# REMANUFACTURING MODELING *and* ANALYSIS

Mehmet Ali Ilgin
Surendra M. Gupta

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*To our families:*

*Hulya Ilgin and Mahmut Ilgin*

**Mehmet Ali Ilgin**

*Sharda Gupta, Monica Gupta, and Neil Gupta*

**Surendra M. Gupta**

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# Preface

Consumers' ever-growing appetite to acquire new products and their short courtship with them has kept manufacturers busy expending our virgin resources at an alarming rate. This has led to serious depletion of virgin resources and given rise to increasing amounts of waste and pollution. The traditional way of manufacturing, where we use only virgin materials to produce new products and dispose of the used products at the end of their lives, is unsustainable. Many countries and their governments have started to realize this problem and have imposed strict regulations, some of which require the manufacturers to take back their products when products reach the end of their lives. According to these regulations, the collected end-of-life (EOL) products must also be processed in an environmentally friendly manner. This has forced manufacturers to establish dedicated facilities for product recovery, which involves the minimization of waste amounts sent to landfills by recovering parts and materials from EOL products via remanufacturing and recycling.

In remanufacturing, the collected EOL products are transported to a remanufacturing plant where they are disassembled into parts. Following the cleaning and inspection of disassembled parts, repair and replacement operations are performed to deal with defective and worn-out parts. Finally, all parts are reassembled into a remanufactured product, which is expected to function like a new product. In addition to repair and replacement, some parts or modules may also be upgraded while remanufacturing a product.

Remanufacturing is the most environment-friendly and profitable product recovery option because it has many advantages over other recovery options such as recycling, repairing, or refurbishing. In remanufacturing, a majority of labor, energy, and material values embedded in an EOL product are recovered because the disassembled parts are used "as is" in the remanufacturing process. On the other hand, in recycling, only the material is recovered because the EOL products are simply shredded in a recycling facility. Remanufactured products provide superior performance due to replacement of worn-out parts and upgrading of some key parts. That is why many manufacturers are willing to give consumers the same warranty provisions as with new products. Although replacement of some parts may occur during the repair or refurbishment option, there is no upgrading. Therefore, repaired or refurbished products may not provide a superior performance, and their warranty provisions are inferior to those of the remanufactured or new products.

While the history of remanufacturing dates back to the 19th century, it was used more systematically during World War II when many manufacturers diverted their regular product lines to military products. This led to an increase in the use of remanufactured products as countries experienced shortage of materials. Although the importance of remanufacturing diminished somewhat during the decades that followed World War II, as western countries flirted with the idea of throw-away products, they soon started doubting the sustainability of this practice. As a consequence, there has been a renewed interest in remanufacturing during the past decade, and an increase in the number of companies embracing remanufacturing has ensued because of its environmental and monetary advantages. Today, the size of the US remanufacturing industry is in the billions of dollars. Expansion of the remanufacturing industry has sparked research activities in the problems faced by remanufacturers. Academicians have started to address various design, planning, and processing issues encountered in remanufacturing systems. Among these issues, the following are the most prominent and common to all remanufacturing systems: product design, logistics network design, selection of used products, evaluation of remanufacturing facilities, forecasting, scheduling, inventory management, production planning, capacity planning, pricing, control mechanisms, uncertainty management, product acquisition management, supplier evaluation, optimal supplier portfolio, selection of third-party logistics providers, performance measurement, disassembly, cleaning, inspection, and reassembly.

In this book, we discuss the above issues and provide examples of quantitative modeling methodologies to deal with them. The majority of these methodologies are based on popular industrial engineering and operations research techniques such as material requirements planning, the kanban system, cost–benefit analysis, house of quality, analytical hierarchy process, orthogonal arrays, simulation modeling, linear integer programming, goal programming, linear physical programming, dynamic programming, and queuing theory.

The issues addressed in this book can serve as foundations for researchers to build bodies of knowledge in these fast growing areas of remanufacturing systems. Moreover, practitioners can utilize the models proposed in this book to analyze a particular remanufacturing issue.

This book is organized as follows:

In Part I (Background), Chapter 1 provides an introduction to remanufacturing by presenting information on history, industry size and potential, comparison with other end-of-life options, benefits, conditions, challenges, and steps in a typical process. Chapter 2 presents brief information on each of the industrial engineering and operations research techniques used in different chapters of the book. In Part II (Design Issues), Chapter 3 explains the models developed to increase the remanufacturability of product designs. Chapter 4 proposes models that use goal programming, linear physical programming, and linear integer programming to design reverse and closed-loop supply chains. In Chapter 5, models that use linear integer programming, cost–benefit analysis, and linear physical programming are proposed for the selection of used products. Models developed for the evaluation of remanufacturing facilities are analyzed in Chapter 6. In Part III (Planning Issues), Chapter 7 provides models for the forecasting of product returns. Models on job sequencing are covered in Chapter 8. Chapter 9 proposes models on inventory management. Production planning models are discussed in Chapter 10. Chapter 11 presents capacity planning models. Pricing models are presented in Chapter 12. In Chapter 13, models developed to control a remanufacturing system are discussed. Models presented in Chapter 14 use queuing theory and simulation to deal with the uncertainty problem. In Chapter 15, the models developed for the acquisition of used products are explained. Supplier evaluation and optimal supplier portfolio are discussed in Chapters 16 and 17, respectively. An analytical hierarchy process model is presented for the selection of third-party logistics providers in Chapter 18. In Chapter 19, performance measurement techniques are discussed. In Part IV (Processing Issues), Chapter 20 presents models on various aspects of disassembly (i.e., scheduling, sequencing, line balancing, disassembly to order systems, automation, and ergonomics). Information on cleaning, inspection, and reassembly is provided in Chapters 21, 22, and 23, respectively. Finally, in Part V (Epilogue), Chapter 24 presents conclusions.

# Acknowledgments

There has been a growing interest in remanufacturing during the past decade. An increase in the number of companies embracing remanufacturing has ensued due to its environmental and monetary advantages.

Hence, researchers have developed various algorithms, models, heuristics, and software to solve the problems of remanufacturers. This book is an attempt to capture the state of the art in one volume. To the best of our knowledge, this is the first book written solely on quantitative modeling and analysis of remanufacturing systems.

The knowledge in this book is a collective effort of many people working in the remanufacturing area. In this regard, we thank hundreds of researchers from whose work we have benefited and many of whom we have had the good fortune of meeting and interacting with at conferences around the world.

We want to thank Taylor & Francis for their commitment to publish and stimulate innovative ideas. We also express our sincere appreciation to the Taylor & Francis staff for providing unwavering support at every stage of this project.

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**Mehmet Ali Ilgin, PhD,** is currently on the academic staff of Dokuz Eylul University, Turkey. He will join the Industrial Engineering department of Celal Bayar University, Turkey, as an assistant professor, in August 2012. He holds a PhD in industrial engineering from Northeastern University in Boston, and BS and MS in industrial engineering from Dokuz Eylul University. His research interests are in the areas of environmentally conscious manufacturing, product recovery, remanufacturing, reverse logistics, spare parts inventory management, and simulation. He has published a number of research papers in refereed international journals such as *Computers and Industrial Engineering, Robotics and Computer Integrated Manufacturing* and the *International Journal of Advanced Manufacturing Technology*.

**Surendra M. Gupta, PhD,** is a professor of mechanical and industrial engineering and the director of the Laboratory for Responsible Manufacturing, Northeastern University. He has authored or coauthored well over 400 technical papers published in books, journals, and international conference proceedings. Dr. Gupta has taught over 100 courses in such areas as operations research, inventory theory, queuing theory, engineering economy, supply chain management, and production planning and control. Among the many recognitions received, he is the recipient of an outstanding research award and the Outstanding Industrial Engineering Professor Award (in recognition of teaching excellence) from Northeastern University, as well as a national outstanding doctoral dissertation advisor award.

# Part I

# Background

# 1

# *Introduction and Overview*

## 1.1 History

Transformation of one steam frigate into an ironclad ship in 1861 (Anonymous, 2006) is the first known application of remanufacturing. However, the application of remanufacturing on a large scale became possible during World War II in the United States and the United Kingdom. At that time, there was no new car and spare part production in these countries since all production facilities were dedicated to the production of war equipment. So, remanufacturing was extensively used to keep the old cars running (Steinhilper and Brent, 2003).

## 1.2 Size and Potential

New and stricter government regulations on end-of-life (EOL) product treatment and increasing public awareness toward environmental issues have forced many manufacturers to establish specific facilities for remanufacturing operations. There are 70,000 remanufacturing companies in the United States creating \$53 billions per year income, and nearly half million people are employed by these firms. It must be noted that these estimates do not include the remanufacturing activities of US Department of Defense, which frequently remanufactures various military equipment (Lund, 1998; Bras, 2007).

High profit margins amounting to nearly 20% is another reason for the increased attractiveness of remanufacturing. The price of a remanufactured item is generally 30%–40% of a new one. Especially in lesser developed markets, remanufactured items with cheaper prices become very attractive to consumers. Besides high sale numbers, there are important cost savings in remanufacturing. For instance, estimated remanufacturing-related cost savings of Xerox was \$76 million in 1999. The same company had already saved around \$200 million in 1991 from the remanufacture of copiers returned at the end of the lease period (Guide et al., 2003; Bras, 2007; Mukherjee and Mondal, 2009).

The sector with the highest level of involvement in remanufacturing is the automotive sector. According to Steinhilper (2001), remanufacturing activities associated with automotive products stand for two-thirds of all remanufacturing. The remanufacturing of automobile parts (e.g., engines, alternators) is nearly equal to 10% of total production in Germany (Bras, 2007).

## 1.3 Comparison with Other EOL Options

Remanufacturing is the process of bringing an assembly to like-new condition through replacing and rebuilding its components at least to current specification. It offers many advantages over other recovery options. In this section we compare remanufacturing and other recovery options. First, we give the definitions of the alternative recovery options:

- Repair is the process of bringing damaged components back to a functional condition.
- Reconditioning is the process of restoring components to a functional/ and or satisfactory state, but not above original specification, using such methods as resurfacing, repainting, sleeving, etc.
- Recycling is the process of taking component material and processing them into the same material or useful degraded material (Ijomah et al., 1999).

Remanufacturing differs from repair and reconditioning in the following four ways (Ijomah, 2010):

1. Warranties given to remanufactured products are superior to the warranties given to repaired and reconditioned ones. In repair, warranty is given only to the repaired components. In reconditioning, warranty applies to all major wearing parts. On the other hand, in remanufacturing, all parts of the product are within the scope of the warranty.
2. Remanufactured products have higher levels of quality and performance than repaired or reconditioned products since they involve greater work content.
3. In remanufacturing, products may lose their identity since all components of the product are checked and any component that cannot be remanufactured is replaced with a new component. However, in repair and reconditioning, products retain their identities.
4. A remanufactured product may involve one or more upgrades, while there is usually no upgrade in a repaired or reconditioned product.

The differences between remanufacturing and recycling can be summarized as follows:

- In remanufacturing, most of the resources (viz., material, energy, labor) used in the manufacture of the product are conserved. However, in recycling, only the material content of a product can be recovered.
- Due to potential quality problems, designers may be unwilling to use recycled material. This reduces the profit margins. However, remanufacturing is much more profitable, especially for large mechanical and electromechanical products (Ijomah, 2010).

## 1.4 Benefits

Remanufacturing can increase the competitiveness as well as the environmental image of a producer by providing the following benefits (Kerr and Ryan, 2001; Giuntini and Gaudette, 2003; Ijomah, 2010):

- Remanufacturing is more profitable than traditional manufacturing since remanufacturing requires less expert labor, energy, materials, and disposal costs than traditional manufacturing.
- In traditional manufacturing, especially in assembly lines, the work environment is monotonous. The work environment in remanufacturing, by comparison, is much more dynamic and varied. Workers have a broader skill set and higher work satisfaction.
- Failure mode information obtained through remanufacturing activities can provide critical information for product design and development projects.
- Remanufacturing facilities can offer job opportunities for retired and laid-off factory workers. These workers can contribute their experience in disassembling and reassembling products they helped build years before.
- Remanufacturing provides consumers with the opportunity to obtain high-quality products at low prices. Prices of remanufactured products are 30% to 40% less than similar new products.
- Remanufacturing uses less energy and natural resources because there is a need for only a fraction of the material processing required of new products since most of the raw materials already exist in their final form. Considering energy consumption, only 15% of the energy used to make the product from scratch is consumed for remanufacturing a product. The estimated worldwide energy savings of remanufacturing in lieu of building new products is 400 trillion

BTUs annually. This much energy can be produced using about 16 million barrels of crude oil (about 350 tankers). Remanufacturing can also be an important factor in the reduction of greenhouse gas emissions as a direct result of energy savings.

- Manufacturers can reduce the financial penalty from environmental legislation by dealing with remanufacturing activities. Since recovered parts from returned products are utilized in remanufacturing, there are important reductions in disposal costs, and a much smaller fraction of the EOL resources needs to be recovered through recycling. In addition, final disposal of products is delayed by extending the life of products.
- Through remanufacturing, fewer resources are used to provide customers with the same level of service. As a result, resource intensity is reduced and the eco-efficiency of product systems is increased.
- Remanufactured products have shorter lead times.

## 1.5 Conditions

For the profitable remanufacture of a product, the product, the producer, and the legal and technological infrastructure of the producer's country should have certain characteristics. We summarize them as follows (Ferguson et al., 2010; Seitz and Peattie, 2004):

- The product should have a long useful life and stable technology. In addition, value-added costs (labor, energy, capital) should constitute a large portion of the product's total cost. For instance, remanufacturability of car engine is very high. A car engine is complex with high-value parts, and its stressful working life can lead to failure long before other major components of a car.
- Collection and recovery of a significant number of returns at a reasonably low cost should be possible.
- Remanufacturers should establish a distribution network and transportation system for supplies needed for remanufacturing as well as finished remanufactured products.
- Remanufacturers should be provided with the state of the art remanufacturing technology and knowhow by trade associations, publications, and universities.
- Remanufacturing activities should be supported by the regulatory environment. There should not be excessive taxation. Product liability, intellectual property, and warranty regulations should not involve any unreasonable risks to the remanufacturer.

## 1.6 Challenges

A remanufacturer has to deal with various challenges regarding product design, marketing, accounting, human resources, and operations–production management. We list these challenges as follows (Giuntini and Gaudette, 2003):

- Designers usually do not consider the ease of disassembly and reassembly while developing a new product. This results in high operational costs or high scrap rates, or both, during the remanufacturing process, and the price advantage offered by remanufactured products is reduced. As a result, the demand for remanufactured products is negatively affected.
- There is no incentive to sales people for offering remanufactured products as alternative solutions to customers. That is why they see remanufactured products as a threat to their commissions, which are given based on the sale of new products.
- Remanufactured products are usually not included in the strategic selling plan. In other words, remanufacturing is carried out only in response to individual customer requests. Some companies start remanufacturing activities only to prevent small, independent, unauthorized enterprises from damaging the company's brand name due to the poor quality of remanufacturing.
- Part requirements for a product to be assembled can be determined exactly in traditional manufacturing. Furthermore, assembly of new parts with required tolerance can be carried out smoothly. However, in remanufacturing, the estimation of new part requirements is extremely difficult since new parts are used if there are not enough used parts. The number and condition of used parts can be determined through testing and inspection only after disassembling them from returned products. This results in stochastic routings and lead times. Another detail complicating production planning in remanufacturing systems is the imperfect correlation between supply of returned products and demand for remanufactured products (Gungor and Gupta, 1999; Guide et al., 1999; Guide, 2000; Ilgin and Gupta, 2010; Lage and Godinho-Filho, 2011).
- Remanufacturing requires broader technical skills. However, the existing work force has been trained according to the needs of mass production, which requires worker specialization. Hence, there is a shortage of many skills unique to remanufacturing.
- Metrics developed for producing new products give importance to revenue growth rather than profit growth. However, in remanufacturing, despite the lower sales revenues, profits are often greater in absolute terms and as a percentage of sales.

- Since performance metrics are driven by new-condition product labor productivity, little attention is given to improving remanufacturing-related productivity problems.
- Advertising campaigns are usually designed to stimulate consumers to buy the latest or greatest new technology. There is a need to educate consumers that remanufactured products can be as good as brand new products.
- Physical lives of capital goods are usually longer than their tax depreciation timelines. Since these assets will have a zero book value at the end of the depreciation period, expenditures to extend their lives through remanufacturing are often not given budgeting priority.
- Accounting techniques used to report remanufacturing activities are not well developed. Poorly configured balance sheets and income statements prepared using these techniques give top managers an inaccurate perception of the financial performance of remanufacturing activities.

## 1.7 Remanufacturing Process

Although processing steps may vary depending on the type of the product being remanufactured, the following steps are common in most of the remanufacturing facilities:

- *Cleaning, inspection, and sorting*: The products collected from consumers are cleaned, inspected, and sorted into two categories: good condition and severely damaged. Severely damaged products are sent to a recycling facility directly. Good condition products are disassembled.
- *Disassembly*: Products are separated into their components and subassemblies through disassembly. Disassembled parts and subassemblies are inspected. If a part or a subassembly is not in good condition, it is directly sent to a recycler or to a disposal facility. Repairable parts or subassemblies are repaired. Good-condition and repaired parts and subassemblies are sent to the part-subassembly inventory. Depending on the part demand, new parts procured from suppliers can also be added to the part-subassembly inventory.
- *Reassembly:* A remanufactured product is reassembled using the subassemblies and parts from the part-subassembly inventory. The resulting product is inspected. If it is not functional, it is cleaned and disassembled into its parts and subassemblies again. Functional products are packaged and sent to the remanufactured product inventory.

Figure 1.1 presents the flowchart of a typical remanufacturing process.

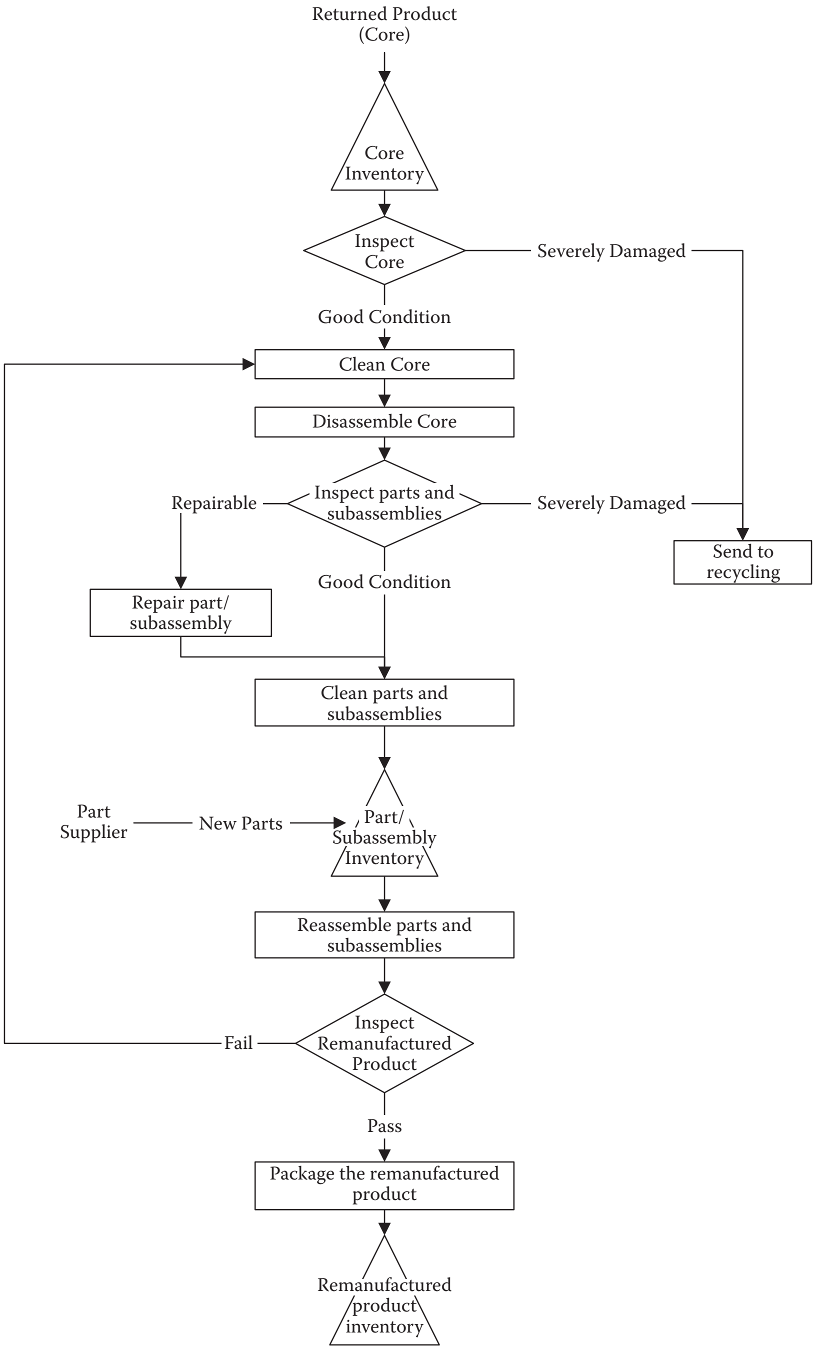

**FIGURE 1.1**
Remanufacturing process.

## 1.8 Overview of the Book

This book presents quantitative models of various issues faced by remanufacturers. These issues are investigated under three main categories: design issues, planning issues, and processing issues. Figure 1.2 depicts the topics considered under each main category.

The book has five parts. This part of the book (Part I) provides a background to remanufacturing as well as brief explanations of industrial engineering/operations research techniques used in the book, such as

- Taguchi loss functions
- Analytical hierarchy process
- TOPSIS
- Goal programming
- Fuzzy logic
- Linear physical programming
- House of quality
- Line balancing techniques
- Simulation
- Experimental design and orthogonal arrays
- Maynard operations sequence technique
- Linear integer programming
- Nonlinear programming
- Queuing theory
- Genetic algorithms

Part II is devoted to design issues that involve long-term decisions (years) and to defining the structure of a remanufacturing system. Product design, reverse and closed-loop supply chain design, selection of used products, and evaluation of remanufacturing facilities are the design issues considered in this part.

Part III is devoted to planning issues that involve medium-term decisions (3 months to 1 year) and determine the flexibility and performance of a remanufacturing system. Forecasting, job sequencing, inventory management, production planning and control, capacity planning, pricing, control mechanisms, uncertainty management, product acquisition management, supplier evaluation, optimal supplier portfolio, selection of third-party logistics providers, and performance measurement are the planning issues considered in this part.

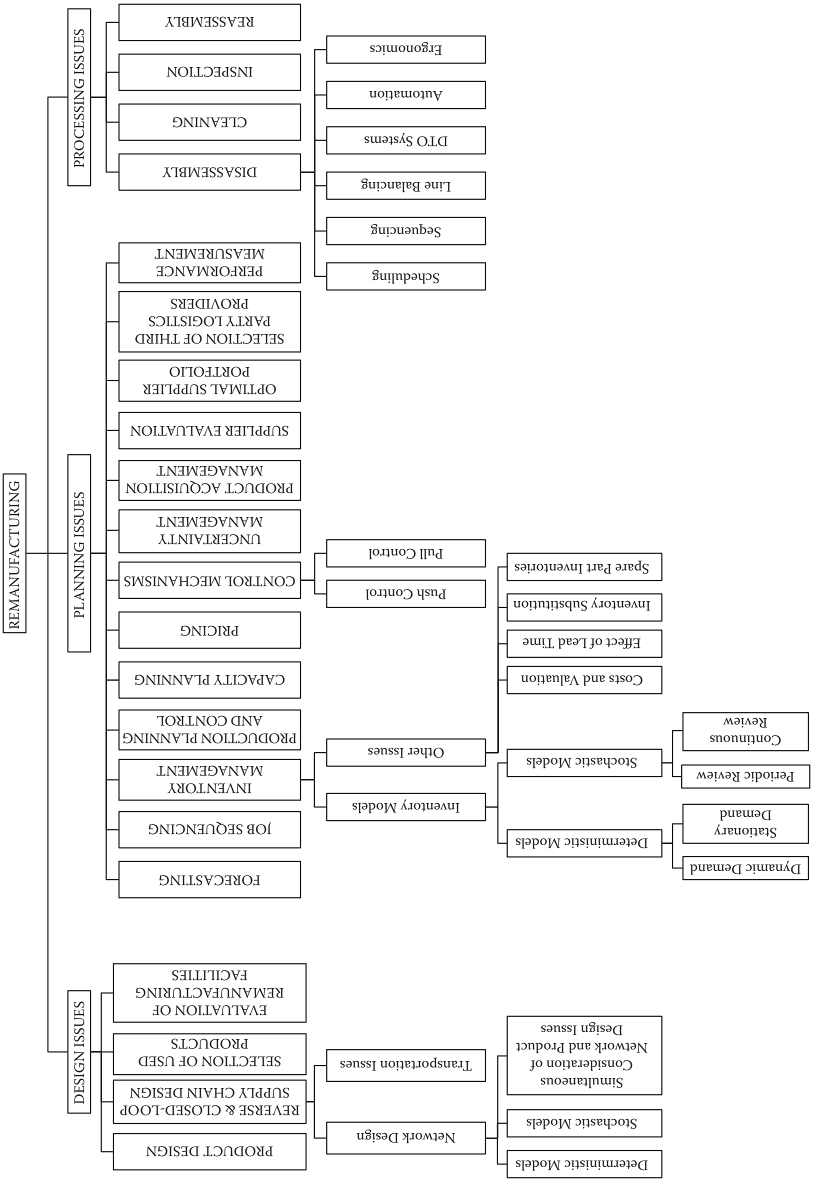

**FIGURE 1.2**
Classification of issues in remanufacturing.

Part IV is devoted to processing issues that involve short-term decisions (minutes, hours, or days) and determine the operational effectiveness of a remanufacturing system. Disassembly, cleaning, sorting and inspection, and reassembly are the processing issues considered in this part.

Concluding remarks are presented in Part V.

## 1.9 Outline of the Book

The book is organized as follows.

In Chapter 2, industrial engineering and operations research techniques used in various remanufacturing models presented in the book are briefly explained.

Part II starts with Chapter 3. In this chapter, four models are presented to address product design issues in remanufacturing. In the first model, an index is proposed to evaluate alternative product designs considering disassembly related product characteristics. The second model proposes a metric to assess the remanufacturability of a product. The third model presents a fuzzy cost–benefit function. The use of house of quality in the remanufacturability analysis of a product design is illustrated in the fourth model. The last section provides a review of other models developed for the evaluation of products considering remanufacturing-related design characteristics.

Chapter 4 presents three models for the design of reverse and closed-loop supply chains. The first model employs goal programming to determine the number of units of used product of each type to be picked for remanufacturing, to identify efficient production facilities, and to achieve the optimal transfer of goods across a closed-loop supply chain in one continuous phase. The second model uses linear integer programming to determine the optimal transportation of products for a generic reverse supply chain involving collection centers, remanufacturing facilities, and demand centers. The third model uses linear physical programming to determine optimal transportation quantities for used and remanufactured products. A review of recent literature on the design of reverse and closed-loop supply chains is provided in the last section.

Chapter 5 presents two models for used-product selection in remanufacturing. The first model uses linear integer programming, while the second model employs linear physical programming. A review of recent literature on used-product selection is provided in the last section.

In Chapter 6, two models are presented for the evaluation of alternative remanufacturing facilities. The first model employs technique for order preference by similarity to ideal solution (TOPSIS), while the second model helps a decision maker calculate the total cost associated with a remanufacturing facility. An overview of other models is also presented in the chapter.

Part III starts with Chapter 7. In this chapter, two models are presented for forecasting product returns in remanufacturing systems. The first model uses traditional forecasting methods, while the second model focuses on novel mathematical formulations developed specifically for the forecasting of product returns. A review of recent literature on forecasting of product returns is provided in the last section.

Chapter 8 focuses on the sequencing of jobs on machines in a remanufacturing facility. First, traditional sequencing rules are analyzed considering the deterministic processing times of remanufacturing jobs. Then the use of simulation in sequencing of remanufacturing jobs is analyzed for the case of stochastic processing times. Finally, an overview of other remanufacturing-related sequencing models is presented in the last section.

In Chapter 9, four models are presented for inventory management in remanufacturing systems. The first model transfers the economic order quantity (EOQ) logic to remanufacturing inventory management. The second model considers both manufacturing and remanufacturing while developing optimal inventory policies. In the third model, a queuing theory–based approach is presented. Finally, the fourth model investigates spare parts inventory management in remanufacturing systems by presenting an integrated approach involving simulation and the genetic algorithm. An overview of remanufacturing inventory models is provided in the last section.

Chapter 10 presents three models for production planning in remanufacturing. The first model develops a production schedule for the remanufacture of a product. In the second model, a material requirements planning (MRP)-based production schedule is developed for disassembled components. The third model considers the use of both newly produced and remanufactured parts/products to meet demand while developing an MRP-based production schedule. An overview of production planning models developed for remanufacturing systems is presented in the last section.

In Chapter 11, a rough-cut capacity planning technique for remanufacturing is presented. A review of the other capacity planning models developed for remanufacturing systems is presented in the last section.

Chapter 12 presents two models for pricing issues in remanufacturing. In the first model, the core prices are determined using the concept of geometric Brownian motion. The second model considers various cases while determining component prices. An overview of the other remanufacturing-related pricing models is presented in the last section.

In Chapter 13, two models are presented for the investigation of control mechanisms in remanufacturing systems. In the first model, the traditional push system is compared with a novel pull-type production control mechanism called the modified kanban system. The second model compares the traditional push system with another novel pull-type control mechanism called the multi-kanban system. An overview of other modified kanban models developed for remanufacturing systems is presented in the last section.

Chapter 14 focuses on uncertainty management in remanufacturing by presenting two models. In the first model, inventory buffers are proposed as a solution for high-level uncertainty associated with remanufacturing systems. The second model evaluates the potential of sensor-embedded products in dealing with uncertainty in remanufacturing systems. The other models of uncertainty management in remanufacturing are reviewed in the last section.

In Chapter 15, two models are presented for product acquisition management. The first model determines the optimal product acquisition quantity using simple mathematical formulas, while buyback policy decisions are analyzed in the second model. A review of studies from the current literature on product acquisition management is also presented in the chapter.

In Chapter 16, a model integrating Analytic Hierarchy Process (AHP) and Taguchi loss functions is presented for the evaluation of suppliers. An overview of other supplier evaluation models is also presented in this chapter.

Chapter 17 presents two models for determining the optimal supplier portfolio. Nonlinear programming is employed in the first model. The second model presents a methodology integrating Taguchi loss functions, AHP, and fuzzy programming. Recent literature is reviewed in the last section.

In Chapter 18, it is shown how AHP can be used for selecting third-party logistics providers. In the last section, an overview of the recent literature on third-party reverse logistics provider selection, green supplier, and project selection is provided.

Chapter 19 investigates the applicability of manufacturing-related performance measures in remanufacturing systems. A queuing theory–based model is also presented for performance measurement of remanufacturing systems. Finally, recent literature is reviewed in the last section.

Part IV starts with Chapter 20, which focuses on various disassembly issues including scheduling, sequencing, line balancing, disassembly to order (DTO) systems, ergonomics, and automation by providing several models and numerical examples. An overview of other disassembly-related models is presented in the last section.

Chapter 21 discusses the cleaning issues in remanufacturing.

Chapter 22 investigates inspection and sorting issues by presenting numerical examples.

In Chapter 23, reassembly issues in remanufacturing are discussed by considering an example reassembly problem.

Part V involves one chapter (Chapter 24), which presents the conclusions of the book.

## 1.10 Conclusions

This chapter presented an introduction to remanufacturing by providing information on various aspects of remanufacturing (viz., history, size, and potential, comparison with other EOL options, benefits, conditions, challenges, and process). Then the overview and outline of the book are presented.

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# 2

# *Industrial Engineering and Operations Research Techniques Used in the Book*

## 2.1 Introduction

This book is on the modeling and analysis of remanufacturing systems. In each chapter of the book, models developed for a specific issue in remanufacturing are presented. The majority of these models make use of various industrial engineering and/or operations research techniques. In this chapter we provide some basic information on these techniques.

This chapter is organized as follows: Sections 2.2 through 2.16 discuss the basic concepts of Taguchi loss functions, analytic hierarchy process, TOPSIS, goal programming, fuzzy logic, linear physical programming, house of quality, line-balancing techniques, simulation, experimental design and orthogonal arrays, Maynard operations sequence technique, linear integer programming, nonlinear programming, queuing theory, and genetic algorithms, respectively. Finally, some conclusions are presented in Section 2.17.

## 2.2 Taguchi Loss Functions

In traditional quality control, upper and lower specification limits are used to determine acceptable products. Any product within the specification limits is acceptable. However, for a customer, a product barely satisfying the specification limit is as good as the product that is barely out of the specification limit (Besterfield et al., 2003).

Dr. Genichi Taguchi, a Japanese mechanical engineer and statistician, proposed the concept of *loss function* to deal with the controversy between the traditional approach and customer behavior. In this concept, any deviation from the target value results in a loss. If the value of a performance measure is same as the target value, the loss is zero. Otherwise, a quadratic function is used to measure the loss.

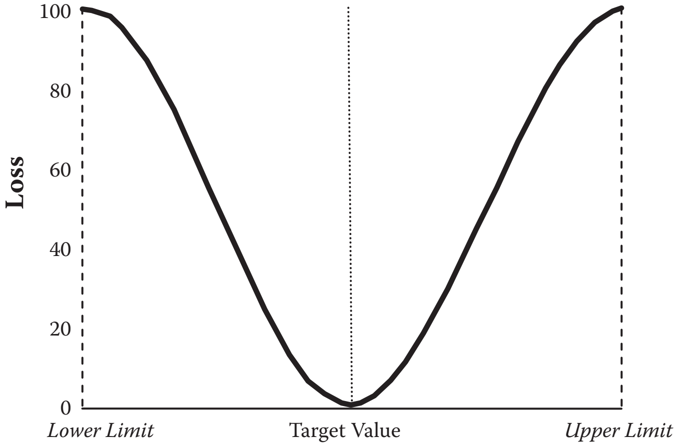

**FIGURE 2.1**
Loss function for "target is best."

Although Taguchi developed more than 68 loss functions (Besterfield et al., 2003), there are three most commonly used Taguchi loss functions, namely, "smaller is better," "target is best," and "larger is better." According to graphical representations of these functions given in Figures 2.1 through 2.3, the loss equation for each of them can be written as follows:

"Target is the best" case:

$$L(y) = k(y - m)^2 \tag{2.1}$$

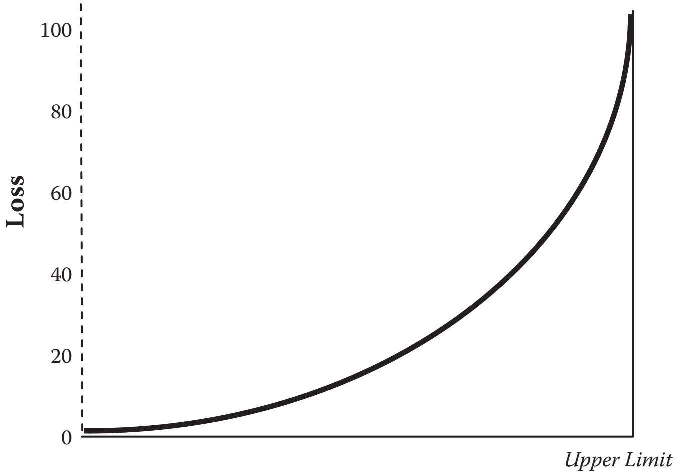

**FIGURE 2.2**
Loss function for "smaller is better."

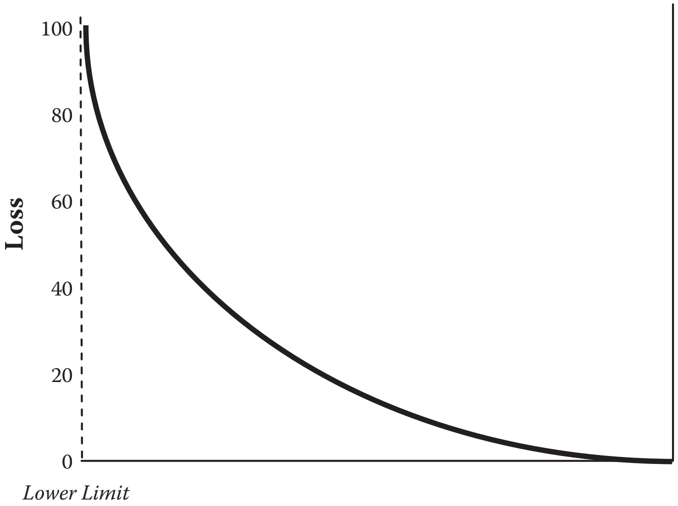

**FIGURE 2.3**
Loss function for "larger is better."

"Smaller is better" case:

$$L(y) = k(y)^2 \tag{2.2}$$

"Larger is better" case:

$$L(y) = k/(y)^2 \tag{2.3}$$

where

$L(y)$ = the loss associated with a particular value of characteristic $y$
$k$ = loss coefficient
$m$ = target value

It must be noted that the value of $k$ is determined by considering the cost at the specification limits and width of the specification.

In the "target is the best" case, loss occurs whenever the performance characteristic departs from the target value, $m$. The target value for the "smaller is better" case is zero, which gives a zero loss, and no negative values exist for the performance measure. In the "larger is better" case, the target value is ∞ (zero loss), and there are no negative values.

## 2.3 Analytic Hierarchy Process

The analytical hierarchy process is a multicriteria decision-making tool formalized by Saaty (Saaty, 1980). It assists decision makers in resolving conflict or setting priorities by comparing tangible and intangible criteria against each other. Due to its mathematical simplicity, a wide range of AHP applications has been presented in the literature, including project management (Mahdi and Alreshaid, 2005), health care (Liberatore and Nydick, 2008), and military personnel assignment (Korkmaz et al., 2008).

The decision problem is defined in a hierarchical way in AHP. There are three levels in the AHP hierarchy. The primary objective is the first level. Independent criteria are considered in the second level. Decision alternatives are placed in the third level. After defining the decision problem, AHP is implemented in two stages. The first stage involves the pairwise comparison of independent criteria based on the scale presented in Table 2.1. The weights of independent criteria are calculated by applying an appropriate mathematical technique (e.g., eigenvalue, mean transformation and row geometric mean) to the matrix of comparative importance values. In the second stage, pairwise comparisons of decision alternatives are carried out for each criterion. The analysis of resulting pairwise comparison matrices with one of the mathematical techniques presented in stage 1 gives the weights of decision alternatives.

The following formula is used to calculate a consistency ratio (CR) for the consistency level of pairwise judgments.

$$CR = \frac{(\lambda_{\max} - N)}{(N-1)R} \tag{2.4}$$

where $N$ is the number of rows (or columns) in the matrix, $\lambda_{\max}$ is the principal eigenvalue of the matrix, and $R$ is the random index value for each $N$ value. Various $R$ values for $N$ values ranging from 1 to 10 are presented in Table 2.2. Perfect consistency is achieved if the value of CR is zero. Due to human errors occurred while comparing alternatives, perfect consistency is

**TABLE 2.1**

Scale of Pairwise Judgments

| Intensity of Importance | Definition |
|---|---|
| 1 | Equally important |
| 3 | Moderately more important |
| 5 | Strongly important |
| 7 | Very strongly more important |
| 9 | Extremely more important |
| 2,4,6,8 | Intermediate judgment values |

**TABLE 2.2**

Random Index Values

| $N$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $R$ | 0 | 0 | 0.58 | 0.90 | 1.12 | 1.24 | 0.32 | 1.41 | 1.45 | 1.49 |

rarely obtained. That is why, any CR value less than 0.1 is considered to be an acceptable consistency level.

## 2.4 TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

TOPSIS is a multicriteria decision-making technique based on the idea that the chosen alternative should have the shortest distance to the ideal solution and the greatest distance from the negative-ideal solution in a Euclidean sense (Hwang and Yoon, 1981). The stages of a TOPSIS study can be presented as follows (Triantaphyllou and Lin, 1996):

Stage 1: *A decision matrix is constructed*. In this matrix (see Table 2.3), each alternative is given a rating with respect to each criterion. If there are $m$ alternatives and $n$ criteria, then the decision matrix can be denoted by $X = (x_{ij})_{m\times n}$, while the relative weight vector for criteria can be presented as $W = (w_1, w_2, \ldots, w_n)$. It must be noted that $\sum_{j=1}^{n} w_j = 1$.

Stage 2: *Decision matrix is normalized.* The following formula is used to calculate an element of the normalized decision matrix $R$:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad i = 1,2,\ldots,m; \quad j = 1,2,\ldots,n \tag{2.5}$$

**TABLE 2.3**

Structure of Decision Matrix in TOPSIS

| | **Criteria 1 ($w_1$)** | **Criteria 2 ($w_2$)** | . . . | **Criteria *n* ($w_n$)** |
|---|---|---|---|---|
| **Alternative 1** | $x_{11}$ | $x_{12}$ | | $x_{1n}$ |
| **Alternative 2** | $x_{21}$ | $x_{22}$ | | $x_{2n}$ |
| . | . | . | | . |
| . | . | . | | . |
| . | . | . | | . |
| **Alternative *m*** | $x_{m1}$ | $x_{m2}$ | | $x_{mn}$ |

Stage 3: *Weighted normalized decision matrix* ($V = (v_{ij})_{m \times n}$) *is constructed* as follows:

$$v_{ij} = w_j \cdot r_{ij}, \qquad i = 1,2,\ldots,m; \quad j = 1,2,\ldots,n \tag{2.6}$$

Stage 4: *The ideal ($A^*$) and negative-ideal ($A-$) solutions are determined* as follows:

$$A^* = \{\max_i v_{ij} \;\; \text{for } i = 1,2,\ldots,m\} = \{p_1, p_2, \ldots, p_n\} \tag{2.7}$$

$$A- = \{\min_i v_{ij} \;\; \text{for } i = 1,2,\ldots,m\} = \{q_1, q_2, \ldots, q_n\} \tag{2.8}$$

Stage 5: *Euclidean distances of each alternative from the ideal solution and the negative-ideal solution are calculated* as follows:

$$E_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - p_j)^2}, \quad i = 1,2,\ldots,m \tag{2.9}$$

$$E_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - q_j)^2}, \quad i = 1,2,\ldots,m \tag{2.10}$$

Stage 6: *Relative closeness of each alternative to the ideal solution is calculated* using the following equation:

$$RCC_i = \frac{E_i^-}{E_i^* + E_i^-}, \quad \text{for } i = 1,2,\ldots,m \tag{2.11}$$

Stage 7: *Alternatives are ranked according to their RCC values.* The alternative with the highest *RCC* value is the best alternative.

## 2.5 Goal Programming

Goal programming is an extension of linear programming in the sense that it can find an optimal solution while dealing with multiple conflicting criteria (Ignizio, 1976). After determining an objective function for each criterion, the sum of the deviations of these objective functions from their respective goals is minimized. The steps in a goal-programming study can be summarized as follows (Steuer, 1986):

- Objectives are conceptualized as goals.
- Priorities and/or weights are assigned to the achievement of the goals.
- A target value is determined for each goal.
- Positive and negative deviation variables are introduced to represent the underachievement and overachievement of goals.
- The desire to overachieve, underachieve, or to satisfy the target value exactly for a goal is determined.

Goal programming models are often classified as preemptive and non-preemptive according to the comparison of goals in importance. Preemptive goal programming requires the decision maker to determine the order of importance of the goals. Then, the goals are satisfied using standard linear programming based on this order. In non-preemptive goal programming, relative weights are assigned to detrimental deviations. These weights can be considered as a per-unit penalty for not meeting a stated goal. Using these weights, the goal-programming model can be converted into a standard linear programming model, minimizing the total weighted deviations from the goals.

## 2.6 Fuzzy Logic

Boolean logic, which is based on two truth values (viz., true and false) is sometimes not appropriate to describe human reasoning. Fuzzy logic (FL), first proposed by Zadeh (1965), is a popular alternative to Boolean logic since it can describe human reasoning by considering the whole interval between 0 (False) and 1 (True). In FL, fuzzy set theory is used to quantify vagueness. In a fuzzy set, each object belonging to the set has a numerical degree of membership in the interval [0,1] based on a membership function. We can define a fuzzy set as follows:

$$\forall x \in X, \qquad {}_A(x) \in [0,1] \tag{2.12}$$

where $A$ is a fuzzy set defined in the universe of quantified linguistic values, $X$. $x$ is a generic element of $X$. ${}_A(x)$ is a membership function associating with each value in $X$, a real number in the interval [0,1]. A membership function value of 1 represents a perfect match between the generic element ($x$) and fuzzy set $A$. A generic element with a membership function of 0 does not belong to the fuzzy set. Membership functions can take many different shapes (e.g., triangular, trapezoidal). Graphical depiction of a triangular fuzzy number (TFN) is given in Figure 2.4.

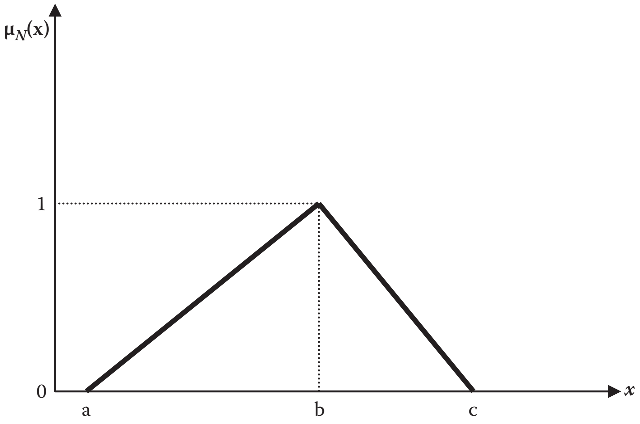

**FIGURE 2.4**
Triangular fuzzy number.

The membership function of a TFN can be defined as follows:

$$ {}_N = \begin{matrix} 0, & x < a \\ (x-a)/(b-a), & a \le x \le b \\ (c-x)/(c-b), & b \le x \le c \\ 0, & x > c \end{matrix} \tag{2.13}$$

A fuzzy number is converted into a crisp real number by means of a technique called defuzzification. There are several defuzzification techniques. The center of area method, a commonly used defuzzification technique, can be implemented for a TFN ($N = (a, b, c)$) as follows (Tsaur et al., 2002):

$$Q = \frac{(c-a)+(b-a)}{3} + a \tag{2.14}$$

The operations defined on TFNs (Chan et al., 2003; Tsaur et al., 2002) can be presented as follows ($N_1 = (a,b,c)$ and $N_2 = (d,e,f)$):

$$\text{Addition operation: } N_1 + N_2 = (a+d,\ b+e,\ c+f) \tag{2.15}$$

$$\text{Subtraction operation: } N_1 - N_2 = (a-f,\ b-e,\ c-d) \tag{2.16}$$

$$\text{Multiplication operation: } N_1 * N_2 = (a{*}d,\ b{*}e,\ c{*}f) \tag{2.17}$$

$$\text{Division operation: } \frac{N_1}{N_2} = \frac{a}{f}, \frac{b}{e}, \frac{c}{d} \tag{2.18}$$

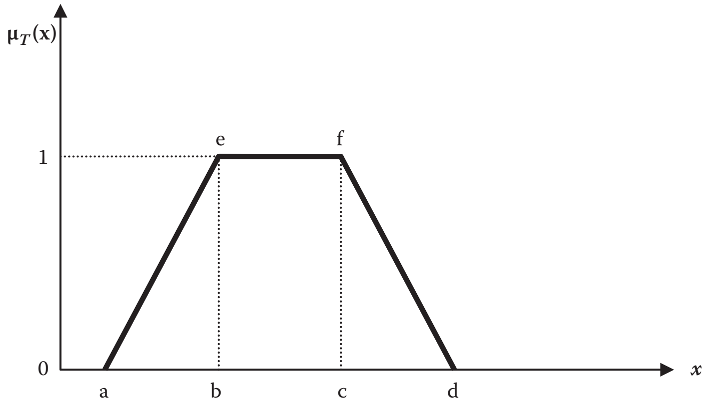

**FIGURE 2.5**
Trapezoidal fuzzy number.

Another commonly used fuzzy number is the trapezoidal fuzzy number, which is graphically depicted in Figure 2.5. We can write the membership function of a trapezoidal fuzzy number as follows:

$$_{T} = \begin{array}{cc} 0, & x < a \\ (x-a)/(b-a), & a \le x \le b \\ 1, & b \le x \le c \\ (d-x)/(d-c), & c \le x \le d \\ 0, & x > d \end{array} \tag{2.19}$$

Defuzzification of a trapezoidal fuzzy number can be carried out using the following formulas under three different cases (Chu and Velásquez, 2009):

If the area *abe* is greater than the area *bdfe*, then the defuzzified trapezoidal fuzzy number is calculated using the following formula:

$$Q = a + \frac{1}{2} \cdot (2a^2 - 2b^2 + 2bc + 2bd - 2ac - 2ad)^{1/2} \tag{2.20}$$

If the area *acfe* is smaller than the area *cdf*, then the defuzzified trapezoidal fuzzy number is calculated using the following formula:

$$Q = d - \frac{1}{2} \cdot (2d^2 - 2c^2 + 2ac + 2bc - 2ad - 2bd)^{1/2} \tag{2.21}$$

In other than the above two cases, the following formula is used:

$$Q = \frac{(a + b + c + d)}{4} \tag{2.22}$$

## 2.7 Linear Physical Programming

Linear physical programming (Messac et al., 1996) is a multicriteria decision-making methodology allowing a decision maker to express his or her preferences with respect to each criterion using four different classes. It is a popular alternative to weight-based methods such as AHP since each criterion can be represented in a more detailed, quantitative, and qualitative way. We can define the soft classes used in LPP as follows:

- Smaller is better (1S)
- Larger is better (2S)
- Value is better (3S)
- Range is better (4S)

The value of the criterion under consideration is given on the horizontal axis, while the function to be minimized for that criterion (*class function*) is placed on the vertical axis. A class function with a lower value is better. Therefore, the ideal value of a class function is zero. Figure 2.6 presents a qualitative and quantitative depiction of four different soft-class functions.

While evaluating an alternative, the preference ranges given in the horizontal axis are used to categorize the value of *i*th criterion. For instance, we can present these ranges for Class 2S in order of increasing preference as follows:

- $g_p \le t_{p5}^-$ (Unacceptable range)
- $t_{p5}^- \le g_p \le t_{p4}^-$ (Highly undesirable range)
- $t_{p4}^- \le g_p \le t_{p3}^-$ (Undesirable range)
- $t_{p3}^- \le g_p \le t_{p2}^-$ (Tolerable range)
- $t_{p2}^- \le g_p \le t_{p1}^-$ (Desirable range)
- $g_p \ge t_{p1}^-$ (Ideal range)

The preferences associated with the *i*th generic criterion are represented by the quantities $t_{p5}^-$ through $t_{p1}^-$, which have physically meaningful values. For instance, a preference vector for the profit criterion can be determined by specifying $t_{p5}^-$ through $t_{p1}^-$ in dollars as (500, 1000, 2000, 3000, 4000). According

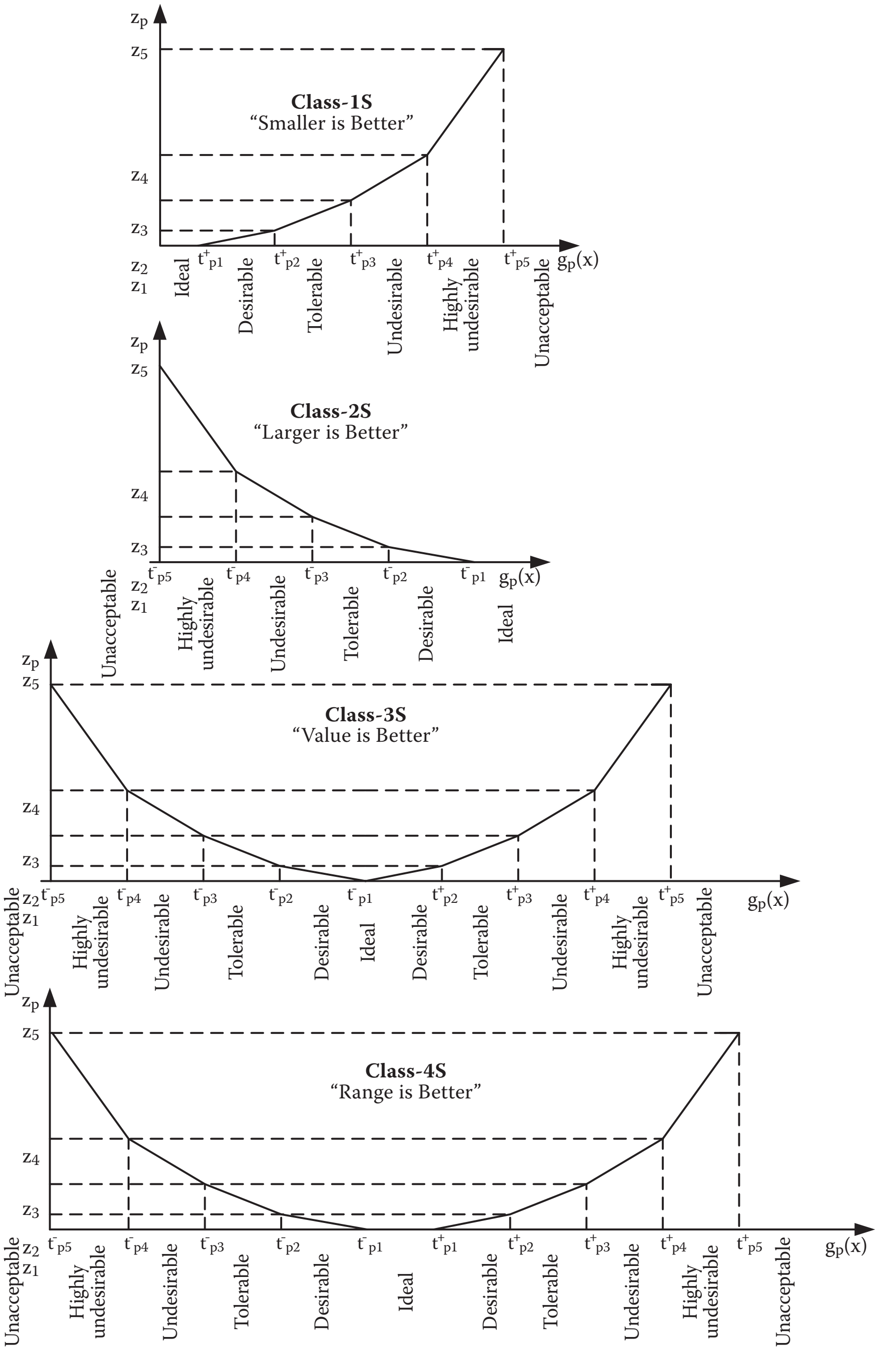

**FIGURE 2.6**
LPP soft-class functions.

to this vector, an alternative with a profit of \$300 would lie in the unacceptable range; an alternative with a profit of \$3400 would lie in the desirable range, and so on.

The following four steps are followed while applying linear physical programming:

1. One of the four classes is specified by the decision maker (DM) for each criterion.
2. The limits of the ranges of differing degrees of desirability (see Figure 2.6) are defined by the DM for each criterion.
3. Based on the DM's preferences defined in steps 1 and 2, the LPP weight algorithm is used to calculate incremental weights, $w_{pr}^{+}$ and $w_{pr}^{-}$, that are related to the class function slopes. Note that the range intersection is represented with $r$ (Messac et al., 1996).
4. A total score ($J$) for each alternative is calculated as a weighted sum of deviations over all ranges and criteria as follows:

$$J = \sum_{p=1}^{P} \sum_{r=2}^{5} (w_{pr}^{-} \cdot d_{pr}^{-} + w_{pr}^{+} \cdot d_{pr}^{+}) \tag{2.23}$$

where

$d_{pr}^{-}$: Negative deviation associated with the $p$th criterion value of the alternative of interest

$d_{pr}^{+}$: Positive deviation associated with the $p$th criterion value of the alternative of interest

$P$: The total number of criteria

It must be noted that the decision alternative with the lowest total score value is the most desirable alternative.

## 2.8 House of Quality

House of quality is a quality planning tool employed to translate customer requirements (voice of the customer) into engineering or technical characteristics. We can summarize the stages required for the development of a basic house of quality as follows (Besterfield et al., 2003):

### 2.8.1 Stage 1: Determination of Customer Requirements

At this stage, the expectations of customers from the product being analyzed are collected through the use of different tools (e.g., surveys).

### 2.8.2 Stage 2: Determination of Technical Descriptors

Technical descriptors or engineering characteristics that will have an effect on at least one of the customer requirements are decided by a team of experts at this stage.

### 2.8.3 Stage 3: Construction of a Relationship Matrix between Customer Requirements and Technical Descriptors

Relationships between customer requirements and technical descriptors are defined in this stage.

### 2.8.4 Stage 4: Construction of an Interrelationship Matrix between Technical Descriptors

This stage involves the development of an interrelationship matrix between Technical Descriptors. This matrix is called the correlation matrix and forms the roof of the house of quality.

### 2.8.5 Stage 5: Competitive Assessments

In the competitive assessments sections of the house of quality, the competitors' products are compared with the product being analyzed. There are two sections for competitive assessments: customer assessment and technical assessment.

The section associated with customer competitive assessment is placed on the right side of the relationship matrix developed in Stage 3. It shows the position of the company compared to its competitors regarding each customer requirement. In this section, the numbers 1 through 5 are used for rating the company and its competitors (1: worst, 5: best).

The technical competitive assessment section is placed under the relationship matrix. It is used to evaluate the company and its competitors for each technical descriptor. As in the case of customer competitive assessment, the numbers 1 through 5 are used for rating the company and its competitors (1: worst, 5: best).

### 2.8.6 Stage 6: Development of Prioritized Customer Requirements

The prioritized customer requirements section is placed on the right side of the customer competitive assessment section. This section involves blocks devoted to "importance to customer," "target value," "scale-up factor," "sales point," and "absolute weight."

- *Importance to Customer* is the evaluation of each customer requirement based on its importance to customers. Numbers 1 through 10 are used to rate each customer requirement (1: the least important, 10: the most important).

- *Target Value* shows the rating value targeted by the company for each customer requirement. It is on the same scale with customer competitive assessment.
- *Scale-up Factor* is calculated by dividing the target value by the rating given in the customer competitive assessment section for the company's product.
- *Sales Point* shows the sale potential of a customer requirement. It takes values between 1 (the lowest potential) and 2 (the highest potential).
- *Absolute Weight* is calculated as follows:

$$\begin{aligned}\text{Absolute Weight} = {} & (\text{Importance to Customer}) \\ & (\text{Scale-up Factor})(\text{Sales Point})\end{aligned} \tag{2.24}$$

### 2.8.7 Stage 7: Development of Prioritized Technical Descriptors

The prioritized technical descriptors section is placed under the technical competitive assessment section. This section involves blocks devoted to "degree of difficulty," "target value," "absolute weight," and "relative weight."

- *Degree of Difficulty* shows the technical difficulty associated with the implementation of a technical descriptor. Numbers 1 (the least difficult) through 10 (the most difficult) are used to rate each technical descriptor.
- *Target Value* shows the rating value targeted by the company for each technical descriptor. It is on the same scale as technical competitive assessment.
- *Absolute Weight* for the $j$th technical descriptor is calculated as follows:

$$a_j = \sum_{i=1}^{n} R_{ij} c_i \tag{2.25}$$

where

$a_j$ : row vector of absolute weights for the technical descriptors ($j = 1, \ldots, m$)
$R_{ij}$: weights in the relationship matrix ($i = 1, \ldots, n, j = 1, \ldots, m$)
$c_i$ : column vector of importance to customer values ($i = 1, \ldots, n$)
$m$ : number of technical descriptors
$n$ : number of customer requirements

- *Relative Weight* for the $j$th technical descriptor is calculated as follows:

$$b_j = \sum_{i=1}^{n} R_{ij} d_i \tag{2.26}$$

where

$b_j$: row vector of relative weights for the technical descriptors ($j = 1, \ldots, m$)
$d_i$: column vector of absolute weights for the customer requirements ($i = 1, \ldots, n$)

Engineering efforts must be concentrated on the technical descriptors with high absolute and relative weights.

## 2.9 Line-Balancing Techniques

Line balancing is the allocation of the total workload on an assembly line to workstations as evenly as possible to achieve a higher utilization of labor and equipment. The amount of time available at each workstation to complete its assigned tasks is the cycle time ($L_c$). $L_c$ can also be interpreted as the time interval at which a product is completed. The following formula is used to determine $L_c$.

$$L_c = \frac{\text{Available Time}}{\text{Production Rate}} \tag{2.27}$$

In this formula, available time and production rate must be calculated for the same time period (e.g., hour, day, etc.).

The theoretical minimum number of stations in an assembly line can be determined using the following formula:

$$N = \frac{\text{Work Load/period}}{\text{Available Time/period}} \tag{2.28}$$

Work Load is determined by multiplying the production rate by the work content time (WCT), which is the total amount of time required to make one assembled product. WCT is equal to the sum of work element times:

$$WCT = \sum_{k=1}^{n_{we}} wet_k \tag{2.29}$$

where $n_{we}$ is the number of work elements, and $wet_k$ is the time required to perform work element $k$.

Efficiency of a line-balancing solution is determined by dividing work content time by the total available service time on the line as follows:

$$E = \frac{WCT}{N \cdot ST} \tag{2.30}$$

where $E$ is the balance efficiency, and $ST$ is the maximum station time. The denominator in this formula gives the total service time spent for the assembly of one product. A perfect line balance ($E = 1$) is achieved when the numerator (work content time) and the denominator (total service time) are equal to each other.

The following expressions can be used to represent the objective of line balancing mathematically (Groover, 2008):

$$\text{Minimize} \quad (N \cdot ST - WCT) \quad \text{or} \quad \text{Minimize} \quad \sum_{i=1}^{N} (ST - ST_i) \tag{2.31}$$

subject to

(1) $ST_i \leq ST \quad \textit{for} \quad i = 1, 2, \ldots, N$
and
(2) all precedence requirements are obeyed

where $ST_i$ is the service time at station $i$.

In this book we consider three line-balancing algorithms (viz., largest-candidate rule, ranked positional weights methods, and the Kilbridge and Wester method).

### 2.9.1 Largest Candidate Rule

Before starting this algorithm, work elements are listed in descending order according to their $wet_k$ values. Then the following steps are completed:

1. Starting from the top of the list, select the first element that satisfies precedence relationships while not causing the total sum of $wet_k$ at that station to exceed the allowed $ST$. After assigning a work element to the station, go back to the top of the list to assign other work elements.
2. When there is no work element that can be assigned without exceeding $ST$, then open a new station.
3. Continue implementing steps 1 and 2 until all work elements are assigned.

### 2.9.2 Ranked Positional Weights Method

In this method, a ranked positional weight (RPW) is calculated for each work element by summing the $wet_k$ value of a work element and all other times for work elements that follow this work element in the arrow chain of the precedence relationships diagram. After listing the work elements in the descending order of their RPW values, the three steps presented in the largest-candidate rule are implemented.

### 2.9.3 Kilbridge–Wester Method

In the Kilbridge–Wester method (Kilbridge and Wester, 1961), the position of work elements in the precedence diagram is the main criterion during the assignment process. After drawing the precedence diagram, all elements with no predecessors are grouped in a column, and this column is numbered as I. Next, the elements immediately following the elements included in column I are grouped into column II. This procedure is continued until a complete list of elements grouped into columns is obtained. Then, this three-step procedure is applied to this list.

It must be noted that all of the foregoing line-balancing techniques are heuristic procedures. Hence, the solutions proposed by these techniques are not necessarily optimal.

## 2.10 Simulation

Simulation is a powerful tool used in the analysis of complex processes or systems. It involves the development and analysis of models that have the ability to imitate the behavior of the system being analyzed. After validation, a simulation model can be used mainly for the following three purposes (Pegden et al., 1995):

- Analysis of system behavior
- Development of theories and/or hypothesis based on observed behavior
- Prediction of future behavior

There are several steps to be followed for a successful simulation study. They are as follows (Law, Pegden et al. 1995; Banks et al. 2001; 2007):

- Define and formulate the problem.
- Set the objectives and overall project plan.
- Collect input data.
- Formulate the model representation.

- Translate model representation into modeling software.
- Verify (debug) the simulation computer program.
- Make pilot runs
    - to validate the model to make sure that it produces reasonable results.
    - to determine the length of the initialization period, the length of simulation runs, and the number of replications to be made for each run.
- Make production runs.
- Analyze output data.
- Document and report the results.
- Implement the results.

As indicated in Law (2007), a simulation study is not necessarily a sequential application of the foregoing steps. If there is a need, a simulation analyst can return to a previous step.

Simulation models can be classified into three categories based on the changes in system state:

- Discrete-event simulation models (System state changes at discrete points in time)
- Continuous simulation models (System state changes continuously over time)
- Combined discrete-continuous simulation models (System state changes both continuously over time and at discrete points in time)

A simulation program can be developed either using a programming language (e.g., C, C++, Visual Basic) or a simulation package. The two most commonly used simulation packages are Arena (Kelton et al., 2007) and Extend (Laguna and Marklund, 2004). All simulation models presented in this book are discrete-event simulation models developed in Arena.

## 2.11 Experimental Design and Orthogonal Arrays

In an experimental design study, the values of several product or process parameters are changed across experiments in order to determine the parameters having significant impact on a performance measure of interest. In experimental design terminology, parameters are called *factors,* and parameter values are called *levels,* while the performance measure is termed as *response* (Phadke, 1989; Law, 2007).

While analyzing the results of an experimental design study, the main and interaction effects of factors are considered. The main effect is the separate effect of each factor. If the effect of a factor depends on the level of another factor, then an interaction effect considering these two factors is calculated.

Determination of the number of experiments is an important issue in experimental design. If there are $k$ factors all with two levels, then the number of experiments required to obtain all main and interaction effects can be calculated using the following formula:

$$N = 2^k \tag{2.32}$$

where $N$ is the number of experiments. According to the foregoing formula, $N$ increases geometrically as $k$ increases linearly. In other words, if there are many factors to be analyzed, the required number of experiments becomes too large. One possible alternative solution is the use of fractional factorial designs which have the ability to give information about the main effects and some interaction effects by covering a fraction of the experiments required by a full-factorial design. For $k$ factors all at two levels, the required number of experiments by a fractional factorial experiment is calculated as

$$N = 2^{k-p} \tag{2.33}$$

where $p$ is the fraction of the full factorial used. There are two important details that damage the practical usability of fractional factorial designs:

1. They require the determination of an appropriate resolution level that is a measure of degree of confounding for main effects.
2. There may not be a fractional factorial design with desired resolution for the number of factors considered (Law, 2007).

In order to avoid the said problems of full and fractional factorial designs, *orthogonal arrays* have been used in various experimental design studies. The only information required to construct an orthogonal array is the number of control factors, their levels, and the desire to study specific interactions (Phadke, 1989). After getting this information, all design points can be found in ready-to-use tables.

## 2.12 Maynard Operations Sequence Technique (MOST)

Maynard Operations Sequence Technique (MOST) is a predetermined time system developed by Zandin (1980) to determine the normal time required for the completion of a particular process. It is based on the fact that most of the activities associated with the handling of an object can be represented with a limited number of motion sequences. There are three basic sequence models in MOST: general move, controlled move, and tool use.

1. General Move: This sequence is used to represent the spatial free movement of an object through the air from one location to the next. There are four actions represented with the following letters: A (Action distance): Primarily horizontal movement of the fingers, hands, or feet. B (Bend): Mainly vertical body motions like standing up or sitting. G (Grasp or gain control): Gaining physical control of one or more objects using fingers, hands, or feet. P (Position or place): Positioning, aligning, or orienting one or more objects.

   The three phases of a specific move sequence can be represented as follows:

$$\underbrace{A\,B\,G}_{\text{Get}}\ \underbrace{A\,B\,P}_{\text{Put}}\ \underbrace{A}_{\text{Return}}$$

   Each parameter is assigned an index value in the form of a subscript. This value depends on the type and motion content of action as well as the conditions under which action is undertaken. Table 2.4 presents the index numbers used in MOST. After determining index values for all parameters, the time value for the sequence is calculated in TMUs (time measurement unit, 1 TMU = 0.036 second) by adding the index values and multiplying the sum by a scale factor of 10. We can take the following move sequence as an example:

$$A_6\ B_6\ G_1\ A_6\ B_0\ P_3\ A_0$$

   where

   $A_6$: Walk 3–4 steps
   $B_6$: Bend and arise
   $G_1$: Grasp a small part
   $A_6$: Walk back to the original position

**TABLE 2.4**

Index Values for Parameters of General Movement Sequence in MOST

| Index Value | A (Action Distance) | B (Body Motion) | G (Gain Control) | P (Placement) |
|---|---|---|---|---|
| 0 | ≤ 2 in. (5 cm) | None | None | Hold<br>Toss |
| 1 | Within reach | None | Grasp light object | Lay aside<br>Loose fit |
| 3 | 1–2 steps | Bend and arise with 50% occurrence<br>Sit without adjustments<br>Stand without adjustments | Grasp object that is heavy or obstructed or hidden or interlocked | Place with adjustments<br>Place with light pressure<br>Place with double placement |
| 6 | 3–4 steps | Bend or arise | | Position blind<br>Position with care<br>Position with precision |
| 10 | 5–7 steps | Sit<br>Stand | | |
| 16 | 8–10 steps | Climb on<br>Climb off<br>Bend and sit<br>Stand and bend<br>Through the door | | |

$B_0$: No body motion
$P_3$: Place the part with adjustment
$A_0$: No motion

The sum of the index values for this sequence is 22. Hence, the standard time is 22 × 10 = 220 TMUs (7.92 seconds).

2. Controlled Move: This move sequence is used if an object is moved when it either remains in contact with a surface or remains attached to another object during the move. In addition to the parameters used in general move, control move has three new parameters: move controlled (M), process time (X), and align (I). We refer the interested reader to Salvendy (2001) for the table associated with controlled move.
3. Tool use: Use of hand tools for cutting, gauging, fastening, or writing is represented with this move sequence. A combination of general move and controlled move are used in this sequence. It also involves the following additional parameters: fasten (F), loosen (L), cut (C), surface treat (S), record (R), think (T), and measure (M). We refer the interested reader to Salvendy (2001) for the table associated with tool use.

## 2.13 Linear Integer Programming

Linear programming (LP) involves the minimization or maximization of a linear objective function subject to linear constraints. The most common application of LP is the allocation of limited resources among competing activities in an optimal way. The canonical representation of an LP model can be given as follows:

$$\begin{aligned} &\text{maximize} \quad c^{T}x \\ &\text{subject to } Ax \le \mathrm{b} \end{aligned} \tag{2.34}$$

where $x$ is the vector of variables, $c$ and $b$ are the vector of coefficients, and $A$ is the matrix of coefficients.

A linear integer programming model is an LP model with an added requirement that all variables be integers. It is extensively used for the various engineering and business applications where the divisibility assumption of LP must be dropped (Hillier and Lieberman, 2005).

## 2.14 Nonlinear Programming

In a nonlinear programming (NLP) problem, the objective function and/or some of the constraints are nonlinear. A general form of nonlinear programming problem can be given as follows (Hillier and Lieberman, 2005):

$$\text{Maximize} \qquad f(\mathrm{x}) \tag{2.35}$$

subject to

$$g_i(\mathbf{x}) \le b_i, \qquad \text{for } i = 1,2,\ldots,m$$

and

$$\mathbf{x} \ge \mathbf{0}$$

where $\mathbf{x} = (\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_n)$ is the vector of variables, and $f(\mathbf{x})$ and $g_i(\mathbf{x})$ are given functions of the $n$ variables. Depending on the characteristics of $f(\mathbf{x})$ and the $g_i(\mathbf{x})$ functions, NLP problems may have different shapes and forms. There is no single algorithm that can be used to solve all types of NLP problems. Hence, specific algorithms have been developed for different types of NLP problems.

## 2.15 Queuing Theory

Queuing theory is the mathematical study of waiting lines. It employs queuing models to represent different queuing systems. Formulas developed for a specific queuing model give information on the performance of the corresponding queuing system (Hillier and Lieberman, 2005).

Figure 2.7 presents the components of a queuing system. Customers coming from a calling population arrive to the queuing system. The size of the calling population can be finite or infinite. Although there is only one server

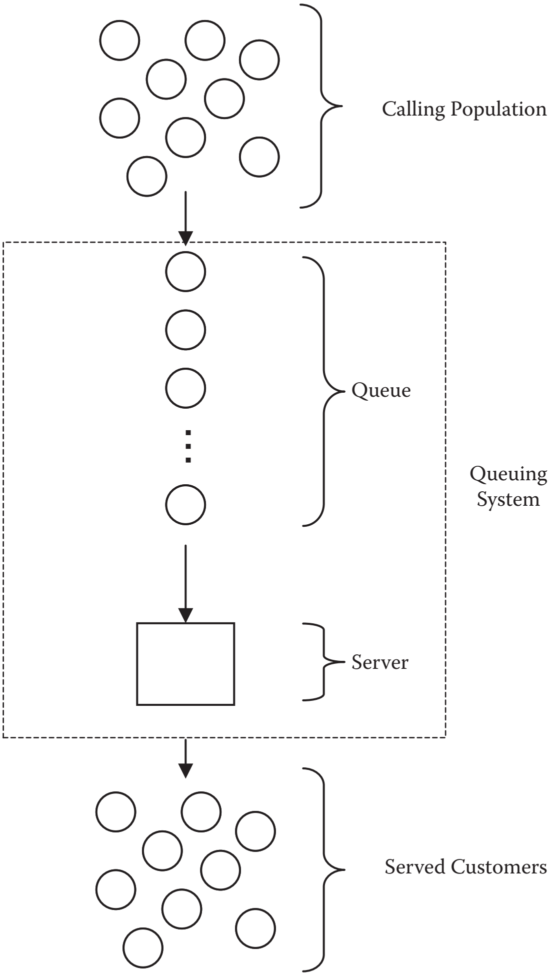

**FIGURE 2.7**
Components of a queuing system.

in Figure 2.7, any number of servers can be considered in a queuing theory problem. If none of the servers is available, customers wait in the queue. After being served, they leave the queuing system.

The following assumptions are used in most of the queuing models besides some specific variations:

- Arrivals occur randomly and independently of other arrivals and according to a Poisson distribution.
- Service times are distributed according to an exponential distribution.
- Only one event can occur at a time.
- The system is in steady-state operation. (i.e., the transient period has been completed).

The following five characteristics are used to describe a queuing system:

1. *Arrival pattern of customers* is characterized by the interarrival time between two consecutive arrivals. This interarrival time can be deterministic or stochastic.
2. *Service pattern* is characterized by the time taken to complete the service. This time can be stochastic or deterministic.
3. *The number of servers.*
4. *The capacity of the system.*
5. *The queue discipline* describes the manner in which customers receive service.

### 2.15.1 Kendall Notation

The characteristics of a particular queuing model can be depicted using the Kendall notation, which involves six tuple (i.e., A/B/C: D/E/F). The different components of this notation can be explained as follows:

First Portion:
  A: Arrival pattern (M: Markovian, D: Degenerate, G: General, $E_k$: Erlang, etc.)
  B: Service pattern (M: Markovian, D: Degenerate, G: General, $E_k$: Erlang, etc.)
  C: Number of servers in parallel
Second Portion:
  D: Service discipline (First in First out FIFO, Last in First out, etc.)
  E: The maximum number of customers allowed in the system
  F: The size of calling population (finite or infinite)

FIFO/∞/∞ is the default configuration for the second portion. If the model is described by this default case, the second portion is often omitted in the Kendall notation. For instance, M/M/c : FIFO/K/∞ (M/M/c/K) is the Kendall notation for the *c* server, finite waiting line (capacity is *K*) queuing system with Poisson arrivals and exponential service time.

### 2.15.2 Little's Law

There are several parameters that describe a queuing system. *L* represents the expected number of customers in the queuing system, while the expected number of customers in the queue itself is given by $L_q$. $W$ and $W_q$ represent the expected time in the queuing system and the expected time in the queue itself, respectively. Little's Law explains the mathematical relationships between these parameters as follows:

$$L = \lambda \cdot W \tag{2.36}$$

$$L_q = \lambda \cdot W_q \tag{2.37}$$

$$W = W_q + \frac{1}{\phantom{\mu}} \tag{2.38}$$

where

λ is the arrival date and μ is the service rate

## 2.16 Genetic Algorithms

Using the principles of both natural selection and natural genetics, genetic algorithms (GAs) search large, nonlinear search spaces where expert knowledge is lacking or difficult to encode and where traditional optimization methods fall short (Goldberg, 1989).

In GA terminology, *population of individuals (chromosomes)* represents the potential solutions to a given problem. A *fitness value* is assigned to each chromosome based on the result of the *fitness (objective) function*. The *selection mechanism* favors individuals of better objective function value to reproduce more often than worse ones when a new population is formed. *Recombination* allows for the mixing of parental information when this is passed to their descendants, and mutation introduces innovation in the population. Usually, the *initial population* is randomly initialized, and the evolution process is stopped after a predefined number of iterations.

The following steps are used in the construction of any type of GA:

- Genetic encoding of solutions
- Forming the initial population

- Determining an appropriate fitness function
- Defining and implementing genetic operators
- Determining the termination criteria

*Encoding:* Chromosome encoding depends on the problem and the type of algorithm. *Binary encoding* (each chromosome is a string of bits, 0 or 1) is the original formulation for GAs. An alternative encoding scheme is *gray encoding*, which is similar to binary encoding except that each successive number only differs by one bit. Some complicated value such as real numbers are used in *direct value encoding*. In *permutation encoding*, a string of numbers representing a position in a sequence forms a chromosome. A chromosome in *tree encoding* is designed as a tree of some objects.

*Forming the initial population:* The initial population is usually created randomly. Besides this, there are several alternative methods. Carrying out a series of initializations for each individual and then picking the highest performing values is one of them. Locating approximate solutions by using other methods (i.e., simulated annealing, tabu search) and starting the algorithm from such points is another alternative (Coley, 2003). Neural networks can also be used to generate the initial population (Reeves, 1995).

*Determining an appropriate fitness function*: The fitness function defines a fitness value for every chromosome in the population. The selection process decides which of the genomes are chosen for reproduction according to this value. The fitness function is a black box for the GA. Internally, this may be achieved by a mathematical function, a simulation model, or a human expert that decides the quality of a chromosome.

*Defining and implementing genetic operators*: There are three main operators to manipulate the genes in a GA chromosome: selection, crossover, and mutation.

- In *selection*, chromosomes are copied considering their fitness function value. There are many selection methods, including roulette wheel selection, Boltzman selection, tournament selection, rank selection, and steady-state selection. Since we use tournament selection in this study, we explain this technique here. In tournament selection, a certain number of individuals is selected randomly from the population, and the best individual from this group is copied into the intermediate population. This process is repeated until the mating pool is complete. Tournaments are frequently held only between two individuals.
- *Crossover* refers to the occasional crossing of two chromosomes in such a way that they exchange equivalent genes with one another.
- The aim of the *mutation* process is to avoid local minima and to ensure that newly generated populations are not uniform and incapable of further evolution (Holland, 1992). In this process, a random

number is generated in the interval [0, 1] and compared with a specified threshold value $P_m$: if it is less than $P_m$, then mutation is carried out for that gene; otherwise the gene is skipped.

*Termination Criterion*: A limit on the number of fitness evaluations or computer clock time can be determined as a termination criterion. Another way is tracking the population's diversity and stopping when this falls below a preset threshold. The meaning of diversity in the latter case is not always obvious, and it could relate either to the genotypes or the phenotypes, or even, conceivably, to the fitnesses, but in any event we need to measure it by statistical means. For example, we could decide to terminate a run if at every locus the proportion of one particular allele rose above 90% (Reeves and Rowe, 2002).

## 2.17 Conclusions

In this chapter, industrial engineering and operations research techniques used in the remanufacturing models presented in different chapters of the book were introduced. One or more of the techniques introduced in this chapter are used by each of these models.

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# Part II

# Design Issues

# 3

# *Product Design*

## 3.1 The Issue

For a new product development team, manufacturability, functionality, and low-cost production of the product are generally the main design criteria. Product features that promote remanufacturing are rarely considered, or they are given lower priority. As a result of this traditional design philosophy, many firms are having difficulties in remanufacturing their own products. High disassembly costs, and difficult-to-disassemble and damaged parts, are the main obstacles faced by them.

These problems are forcing manufacturers to consider remanufacturing-related product characteristics in the design phase of the product. These design for remanufacturing initiatives focus on product characteristics that would facilitate one or more of the following elements of the remanufacturing process:

- Disassembly
- Sorting
- Cleaning
- Refurbishment
- Reassembly
- Testing

Four models are presented in this chapter. In the first model, an index is proposed to evaluate alternative product designs considering disassembly-related product characteristics. The second model proposes a metric to assess the remanufacturability of a product. The third model presents a fuzzy cost–benefit function. The use of house of quality in the remanufacturability analysis of a product design is illustrated in the fourth model. In the last section, an overview of other studies is provided.

## 3.2 Design for Disassembly Index

Disassembly is an important element of remanufacturing since it allows us to separate the parts we need from the core. Any technique developed to evaluate and improve a product design with respect to disassembly is also effective in increasing the remanufacturability of the product. In this section we present a technique developed by Veerakamolmal and Gupta (1999) to analyze the merits and drawbacks of different product designs considering the disassembly process.

The technique measures the efficiency of a product design using an index called design for disassembly index (DfDI). In order to calculate the DfDI for a product, a disassembly tree (DT) is constructed for the product. Precedence relationships that define the structural constraints in terms of the order in which components can be retrieved are identified based on the DT. Then, the DfDI is calculated by analyzing the trade-off between the costs and benefits of EOL disassembly to find the combination of components that provides the optimum cost–benefit ratio for end-of-life retrieval. In this analysis, costs of disassembly (labor) and disposal are compared against the benefit derived from the sale of recovered components and materials.

While determining the best product design, the benefit from retrieving a set of components is weighed against the cost of disposing of the remainders. For instance, retrieval of the motor and condenser, while recycling and disposing of the rest of the components can be a feasible combination (set of components) considering the design of an air conditioner for disassembly.

In addition to the evaluation of the feasible combinations, the combination with the highest cost–benefit from one design must be compared against the others while comparing the merits of two (or more) designs. The best combination is determined by enumerating all combinations with respect to their cost–benefit functions.

The cost–benefit function involving four terms (viz., total resale revenue (*RR*), total recycling revenue (*RCR*), total processing cost (*PC*), and total disposal cost (*DC*) can be written as follows:

$$Z = RR + RCR - PC - DC \tag{3.1}$$

The terms of the function are discussed in the following text.

### 3.2.1 Total Resale Revenue (RR)

*RR* is equal to the difference between the total revenue from the resale of components and the cost of product acquisition. It can be formulated as

$$RR = \sum_{j \;\; P_j \in LS^s(Root_i)} (RV_j \cdot \{M_{ij}\} \cdot \{X_{ij}\}) - TC_i \tag{3.2}$$

where $RV_j$ is the resale value of component *j*, $M_{ij}$ is the multiplicity matrix representing the number of each type of component *j* obtained from each type of product *i*, $X_{ij}$ is the matrix representing the (mutually exclusive combination) selection of component *j* retrieved from product *i* for reuse ($X_{ij} = 1$) or recycle and/or disposal ($X_{ij} = 0$), and $TC_i$ is the cost of acquisition and transportation for product *i* ($/unit).

### 3.2.2 Total Recycling Revenue (RCR)

The component recycling revenue factors and the number of component units recycled for materials content are taken into consideration while calculating *RCR:*

$$RCR = \sum_{j \; P_j \in LS^s(Root_i)} (CI_j \cdot W_j \cdot CRP_j \cdot (M_{ij}) \cdot (1 - \{X_{ij}\})) \cdot CF \tag{3.3}$$

where $CRP_j$ is the percentage of recyclable contents of a component (the portion not recycled must be properly disposed of); $CI_j$ is the recycling revenue index (varying in value from 1 to 10), which is an indicator of the benefit generated by the recycling of a component (a high index value represents more profit); $W_j$ is the weight of the component; and *CF* is the recycling revenue factor.

### 3.2.3 Total Processing Cost (PC)

*PC* is calculated by multiplying the process makespan ($TD_i^s$) by the processing cost per unit time (*UPC*):

$$PC = TD_i^s \cdot UPC \tag{3.4}$$

Assuming that there is a demand for all selected components, $TD_i^s$ can be calculated as follows:

$$TD_i^s = \underset{\forall P_j \in LS^s(Root_i)}{Max} \{X_{ij}\} \quad \cdot (T(Root_i)) + \sum_{k=1}^{s_i} \underset{\forall P_j \in LS^s(SA_{ik})}{Max} \{X_{ij}\} \quad \cdot (T(SA_{ik})) \tag{3.5}$$

where $LS^s(Root_i)$ is the set of selected leaf successors of the root node in product *i*, $LS^s(SA_{ik})$ is the set of selected leaf successors of subassembly node *k* in product *i*, and $T(SA_{ik})$ is the time to disassemble subassembly *k* from product *i* (unit time). Note that $x$ represents the ceiling of *x*.

### 3.2.4 Total Disposal Cost (DC)

The component disposal cost and the number of component units disposed are taken into consideration while calculating *DC*:

$$DC = \sum_{j \ P_j \in LS^s(Root_i)} (DI_j \cdot W_j \cdot (1 - CRP_j) \cdot \{M_{ij}\} \cdot (1 - \{X_{ij}\})) \cdot DF \tag{3.6}$$

where $DI_j$ is the disposal cost index (varying in value from 1 to 10), which is an indicator of the nuisance created by the disposal of a component (a high index value represents more nuisance); $W_j$ is the weight of the component; and *DF* is the disposal cost factor.

### 3.2.5 Procedure for the Calculation of *DfDI*

The following steps are followed while calculating the *DfDI*:

*Step 1:* The predecessor, resale value, multiplicity, weight, recyclable percentage, recycle index, and disposal index for each component are determined.

*Step 2:* Mutually exclusive combination matrix for component selection is generated.

*Step 3:* Acquisition cost of each product ($TC_i$), processing cost/unit time (*PC*), disassembly times ($T(Root_i)$ and $T(SA_{ik})$), recycling revenue factor (*CF*), and disposal cost factor (*DF*) are determined.

*Step 4:* *RR*, *RCR*, *PC*, and *DC* are calculated for each of the mutually exclusive combinations based on the selection of reused components.

*Step 5:* Total benefit, total cost, *DfDI*, and net benefit for each combination are calculated.

### 3.2.6 An Example Application

In this example, we consider two design alternatives: *DSG1* and *DSG2*. Figures 3.1 and 3.2 present the disassembly tree representations of *DSG1* and *DSG2*, respectively. Both alternatives include five identical components.

The foregoing steps can be illustrated for *DSG1* as follows:

*Step 1:* The predecessor, resale value, multiplicity, weight, recyclable percentage, recycle index, and disposal index for each component can be seen in Table 3.1.

*Step 2:* A mutually exclusive combination matrix is presented in Table 3.2.

*Step 3:* The acquisition cost for both products is assumed to be \$10 (i.e., $TC_1 = 10$ and $TC_2 = 10$); disassembly times ($T(Root_i)$ and $T(SA_{ik})$) can

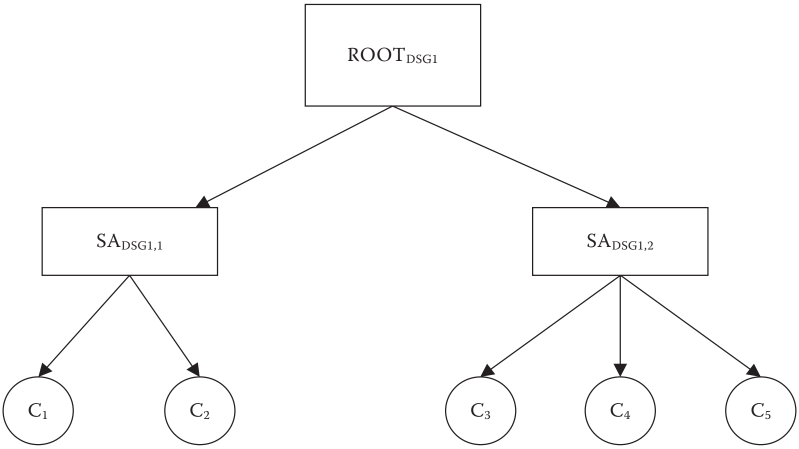


**FIGURE 3.1**
Disassembly tree representation of design alternative *DSG1.*

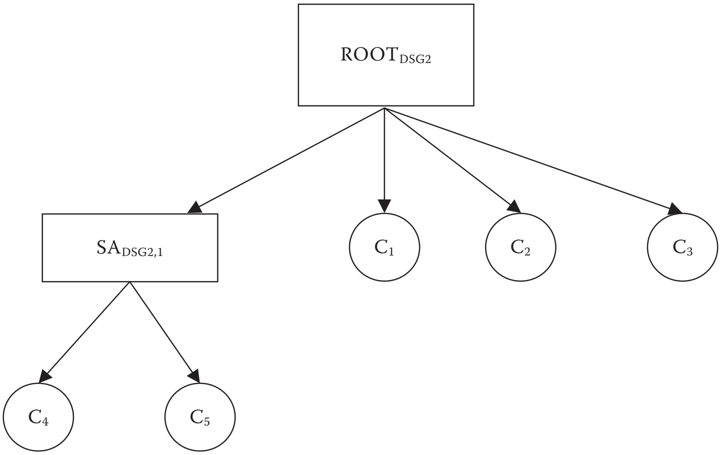


**FIGURE 3.2**
Disassembly tree representation of design alternative *DSG2.*

**TABLE 3.1**

Various Characteristics of Product Design *DSG1*

| Component Code | Predecessor Code | Multiplicity ($M_{ij}$) | Weight ($W_j$) | Resale Value ($RV_j$) | Recyclable Percentage ($RP_j$) | Recycle Index ($RI_j$) | Disposal Index ($DI_j$) |
|---|---|---|---|---|---|---|---|
| C1 | SA$_{DSG1,1}$ | 1 | 2 | 5 | 0.35 | 6 | 4 |
| C2 | SA$_{DSG1,1}$ | 2 | 4 | 8 | 0.7 | 4 | 3 |
| C3 | SA$_{DSG1,2}$ | 3 | 5 | 2 | 0.25 | 3.5 | 5 |
| C4 | SA$_{DSG1,2}$ | 1 | 1 | 3 | 0.4 | 5 | 6 |
| C5 | SA$_{DSG1,2}$ | 1 | 3 | 0 | 0.5 | 6 | 2 |

**TABLE 3.2**

Analyzing the Designs DSG1 and DSG2

| Combination | Reuse, Recycle or Disposal ($X_{ij}$) | | | | | Design DSG1 | | | | | | | | Design DSG2 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | C1 | C2 | C3 | C4 | C5 | Reuse Revenue (RR) | Recycling Revenue (RCR) | Processing Cost (PC) | Disposal Cost (DC) | Total Benefit (RR+RCR) | Total Cost (PC+DC) | DfDI | Net Benefit | DfDI | Net Benefit |
| 1 | 1 | 0 | 0 | 0 | 0 | −5.00 | 9.31 | 3.00 | 7.01 | 4.31 | 10.01 | 0.43 | −5.70 | 0.39 | −6.70 |
| 2 | 0 | 1 | 0 | 0 | 0 | 6.00 | 5.67 | 3.00 | 6.81 | 11.67 | 9.81 | 1.19 | 1.86 | 1.08 | 0.86 |
| 3 | 0 | 0 | 1 | 0 | 0 | −4.00 | 7.52 | 2.40 | 1.90 | 3.52 | 4.30 | 0.82 | −0.78 | 0.60 | −2.38 |
| 4 | 0 | 0 | 0 | 1 | 0 | −7.00 | 9.75 | 2.40 | 7.17 | 2.75 | 9.57 | 0.29 | −6.82 | 0.17 | −13.42 |
| 5 | 0 | 0 | 0 | 0 | 1 | −10.00 | 8.35 | 2.40 | 7.23 | −1.66 | 9.63 | −0.17 | −11.28 | −0.10 | −17.88 |
| 6 | 1 | 1 | 0 | 0 | 0 | 11.00 | 4.83 | 3.00 | 6.29 | 15.83 | 9.29 | 1.70 | 6.54 | 1.54 | 5.54 |
| 7 | 1 | 0 | 1 | 0 | 0 | 1.00 | 6.68 | 4.20 | 1.38 | 7.68 | 5.58 | 1.38 | 2.10 | 1.43 | 2.30 |
| 8 | 1 | 0 | 0 | 1 | 0 | −2.00 | 8.91 | 4.20 | 6.65 | 6.91 | 10.85 | 0.64 | −3.94 | 0.44 | −8.74 |
| 9 | 1 | 0 | 0 | 0 | 1 | −5.00 | 7.51 | 4.20 | 6.71 | 2.51 | 10.91 | 0.23 | −8.40 | 0.16 | −13.20 |
| 10 | 0 | 1 | 1 | 0 | 0 | 12.00 | 3.04 | 4.20 | 1.18 | 15.04 | 5.38 | 2.80 | 9.66 | 2.90 | 9.86 |
| 11 | 0 | 1 | 0 | 1 | 0 | 9.00 | 5.27 | 4.20 | 6.45 | 14.27 | 10.65 | 1.34 | 3.62 | 0.92 | −1.18 |
| 12 | 0 | 1 | 0 | 0 | 1 | 6.00 | 3.87 | 4.20 | 6.51 | 9.87 | 10.71 | 0.92 | −0.84 | 0.64 | −5.64 |
| 13 | 0 | 0 | 1 | 1 | 0 | −1.00 | 7.12 | 2.40 | 1.54 | 6.12 | 3.94 | 1.55 | 2.18 | 0.58 | −4.42 |
| 14 | 0 | 0 | 1 | 0 | 1 | −4.00 | 5.72 | 2.40 | 1.60 | 1.72 | 4.00 | 0.43 | −2.28 | 0.16 | −8.88 |
| 15 | 0 | 0 | 0 | 1 | 1 | −7.00 | 7.95 | 2.40 | 6.87 | 0.94 | 9.27 | 0.10 | −8.32 | 0.06 | −14.92 |
| 16 | 1 | 1 | 1 | 0 | 0 | 17.00 | 2.20 | 4.20 | 0.66 | 19.20 | 4.86 | 3.95 | 14.34 | 4.12 | 14.54 |
| 17 | 1 | 0 | 1 | 1 | 0 | 4.00 | 6.28 | 4.20 | 1.02 | 10.28 | 5.22 | 1.97 | 5.06 | 1.03 | 0.26 |
| 18 | 1 | 0 | 0 | 1 | 1 | −2.00 | 7.11 | 4.20 | 6.35 | 5.11 | 10.55 | 0.48 | −5.44 | 0.33 | −10.24 |
| 19 | 0 | 1 | 1 | 1 | 0 | 15.00 | 2.64 | 4.20 | 0.82 | 17.64 | 5.02 | 3.51 | 12.62 | 1.80 | 7.82 |
| 20 | 0 | 1 | 0 | 1 | 1 | 9.00 | 3.47 | 4.20 | 6.15 | 12.47 | 10.35 | 1.20 | 2.12 | 0.82 | −2.68 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 21 | 0 | 1 | 1 | 0 | 1 | 12.00 | 1.24 | 4.20 | 0.88 | 13.24 | 5.08 | 2.61 | 8.16 | 1.34 | 3.36 |
| 22 | 0 | 0 | 1 | 1 | 1 | −1.00 | 5.32 | 2.40 | 1.24 | 4.32 | 3.64 | 1.19 | 0.68 | 0.42 | −5.92 |
| 23 | 1 | 0 | 1 | 0 | 1 | 1.00 | 4.88 | 4.20 | 1.08 | 5.88 | 5.28 | 1.11 | 0.60 | 0.58 | −4.20 |
| 24 | 1 | 1 | 0 | 1 | 0 | 14.00 | 4.43 | 4.20 | 5.93 | 18.43 | 10.13 | 1.82 | 8.30 | 1.23 | 3.50 |
| 25 | 1 | 1 | 0 | 0 | 1 | 11.00 | 3.03 | 4.20 | 5.99 | 14.03 | 10.19 | 1.38 | 3.84 | 0.94 | −0.96 |
| 26 | 1 | 1 | 1 | 1 | 0 | 20.00 | 1.80 | 4.20 | 0.30 | 21.80 | 4.50 | 4.84 | 17.30 | 2.34 | 12.50 |
| 27 | 1 | 0 | 1 | 1 | 1 | 4.00 | 4.48 | 4.20 | 0.72 | 8.48 | 4.92 | 1.72 | 3.56 | 0.87 | −1.24 |
| 28 | 1 | 1 | 0 | 1 | 1 | 14.00 | 2.63 | 4.20 | 5.63 | 16.63 | 9.83 | 1.69 | 6.80 | 1.14 | 2.00 |
| 29 | 1 | 1 | 1 | 0 | 1 | 17.00 | 0.40 | 4.20 | 0.36 | 17.40 | 4.56 | 3.82 | 12.84 | 1.86 | 8.04 |
| 30 | 0 | 1 | 1 | 1 | 1 | 15.00 | 0.84 | 4.20 | 0.52 | 15.84 | 4.72 | 3.36 | 11.12 | 1.66 | 6.32 |
| 31 | 0 | 0 | 0 | 0 | 0 | −10.00 | 10.15 | 0.00 | 7.53 | 0.15 | 7.53 | 0.02 | −7.38 | 0.02 | −7.38 |
| 32 | 1 | 1 | 1 | 1 | 1 | 20.00 | 0.00 | 4.20 | 0.00 | 20.00 | 4.20 | 4.76 | 15.80 | 2.22 | 11.00 |

**TABLE 3.3**

Disassembly Times of Subassemblies for DSG1 and DSG2

| | Subassembly | Disassembly Time |
|---|---|---|
| Design DSG1 | $\text{Root}_1$ | 2 |
| | $\text{SA}_{11}$ | 3 |
| | $\text{SA}_{12}$ | 2 |
| Design DSG2 | $\text{Root}_2$ | 4 |
| | $\text{SA}_{21}$ | 5 |

be seen in Table 3.3; and processing cost/unit time (*UPC*), recycling revenue factor (*CF*), and disposal cost factor (*DF*) are 0.6, 0.2, and 0.1, respectively.

*Step 4: RR*, *RCR*, *PC*, and *DC* are calculated for each of the mutually exclusive combinations based on the selection of reused components. As an example, for combination number 26, the components selected for resale include $C_1$, $C_2$, $C_3$, and $C_4$. Using Equation (3.2),

$$RR = (5 \cdot 1 \cdot 1 + 8 \cdot 2 \cdot 1 + 2 \cdot 3 \cdot 1 + 3 \cdot 1 \cdot 1) - 10 = \$20$$

The information associated with the components that are not reused (i.e., $C_5$ in combination 26) is employed to calculate total recycling revenue as follows:

$$RCR = (6 \cdot 3 \cdot 0.5 \cdot 1 \cdot 1) \cdot 0.2 = \$1.8$$

In order to harvest the components $C_1$, $C_2$, $C_3$, and $C_4$, subassembly modules $Root_{DSG1}$, $SA_{DSG1,1}$, and $SA_{DSG1,2}$ must be disassembled. Using the disassembly times presented in Table 3.3, the total processing cost can be calculated as follows:

$$PC = (T(Root_{DSG1}) + T(SA_{DSG1,1}) + T(SA_{DSG1,2})) \cdot (0.60) = 4.2$$

Calculation of total disposal cost using Equation (3.6) is presented as follows:

$$DC = (2 \cdot 3 \cdot (1 - 0.5) \cdot 1 \cdot 1) \cdot 0.1 = 0.3$$

The *RR*, *RCR*, *PC*, and *DC* values of every mutually exclusive combination can be seen in Table 3.2.

*Step 5:* Table 3.2 presents the total benefit (*RR* + *RCR*), total cost (*PC* + *DC*), *DfDI* (total benefit – total cost), and net benefit (total benefit – total cost) for each combination.

The highest net benefit value for design *DSG1* is (combination 26) $17.30 with an associated *DfDI* value of 4.84, while the highest net benefit value for design *DSG2* is (combination 16) $14.54 with an associated *DfDI* value of 4.12. Thus, in this case, *DSG1* is preferred due to its higher net benefit and *DfDI* values.

## 3.3 Remanufacturability Metric

Bras and Hammond (1996) developed metrics to evaluate the remanufacturability of a product by considering its design features. A total of eight metrics were developed under four categories. These categories and associated metrics (in parentheses) are as follows:

- Cleaning (cleaning metric)
- Damage correction (refurbishment, key part replacement, and basic part replacement metrics)
- Quality assurance (testing and inspection metrics)
- Part interfacing (assembly and disassembly metrics)

A remanufacturability index is constructed by combining the foregoing metrics. In the following subsections, first, the metrics are explained. Then, the remanufacturability index construction procedure is presented. Finally, a case example is provided in order to illustrate the calculation of metrics and remanufacturability index.

### 3.3.1 Cleaning

Depending on the condition of a part, a range of cleaning processes (viz., loose debris, dry adhered debris, oily debris (baked) and oily debris (washed & dried)) can be applied. While developing the cleaning metric, the different level of investment required by each cleaning process is taken into consideration.

The amount of investment required for each method is compared with that for others in order to generate their relative importance by developing a prioritization matrix (see Table 3.4). In Table 3.5 the definitions of the values used in the prioritization matrix can be seen. Table 3.4 also presents the score, relative importance, approximate cleaning score, and usable cleaning score of each cleaning process. The approximate cleaning scores are then scaled such that the one with the smallest investment (blowing/brushing) is set equal to 1. A total cleaning score can be determined by adding up the individual part’s scores.

**TABLE 3.4**

Prioritizing Cleaning Processes

| | Blown | Abraded | Baked | Washed | Score | Relative Importance | Approximate Cleaning Score | Usable Cleaning Score |
|---|---|---|---|---|---|---|---|---|
| **Blown** | 1.0 | 0.3 | 0.2 | 0.2 | 1.7 | 0.07 | 1.00 (0.07/0.07) | 1 |
| **Abraded** | 3.0 | 1.0 | 0.3 | 0.3 | 4.7 | 0.18 | 2.69 (0.18/0.07) | 3 |
| **Baked** | 5.0 | 3.0 | 1.0 | 1.0 | 10.0 | 0.38 | 5.77 (0.38/0.07) | 6 |
| **Washed** | 5.0 | 3.0 | 1.0 | 1.0 | 10.0 | 0.38 | 5.77 (0.38/0.07) | 6 |

**TABLE 3.5**

Definitions of the Values Used in the Prioritization Matrix

| Value | Definition |
|---|---|
| 5 | (Row) requires much more investment than (column) |
| 3 | (Row) requires more investment than (column) |
| 1 | (Row) requires the same investment as (column) |
| 1/3 | (Row) requires less investment than (column) |
| 1/5 | (Row) requires much less investment than (column) |

The following formula is used to calculate the cleaning metric:

$$\alpha_{\text{Cleaning}} = \frac{IP \cdot 1}{CS} \tag{3.7}$$

where

*IP*: Number of ideal parts
*CS*: Cleaning score

### 3.3.2 Damage Correction

In this category, there are three metrics: refurbishing metric, key part replacement metric, and basic part replacement metric.

#### *3.3.2.1 Refurbishing Metric*

The ideal case occurs when there is no part requiring refurbishing. Similar to the procedure used in the determination of other metrics, the ideal case is achieved when the metric approaches 1. In other words, when the total number of parts not requiring refurbishing becomes equal to the total number of parts, the ideal case is achieved. Considering the fact that the number of parts not requiring refurbishing is equal to the total number of parts minus the number of parts requiring refurbishing, the following formula is used to calculate this metric:

$$\alpha_{\text{Refurbish}} = 1 - \frac{RFP}{TP} \tag{3.8}$$

where

*RFP*: Number of parts requiring refurbishing
*TP*: Total number of parts

#### 3.3.2.2 Key Part Replacement Metric

In each product, there is at least one key part. In the ideal case, none of these key parts is replaced. Based on this information, the metric for key part replacement can be determined using the following formula:

$$\alpha_{\text{Key Replacement}} = 1 - \frac{KPR}{KP} \tag{3.9}$$

where

*KPR*: Number of key parts replaced
*KP*: Number of key parts

#### 3.3.2.3 Basic Part Replacement Metric

While calculating this metric, the number of basic parts requiring replacement is compared to the total number of parts minus the number of key parts. Similar to the key part replacement metric, the ideal case occurs when there is no basic part requiring replacement. The following formula is used to calculate this metric:

$$\alpha_{\text{Basic Replacement}} = 1 - \frac{NR - KPR}{TP} \tag{3.10}$$

where
*NR*: Total number of replaced parts

### 3.3.3 Quality Assurance

Two metrics are considered under this category: testing metric and inspection metric.

#### 3.3.3.1 Testing Metric

While calculating the testing metric, first, a total idealized time for testing is determined by multiplying the total number of tests by 10 seconds. This ideal time is compared to the total actual time required to perform all tests for the product. The following expression is used to calculate the testing metric:

$$\alpha_{\text{testing}} = \frac{NT \cdot 10\,\text{s}}{TT} \tag{3.11}$$

where

*NT*: Total number of tests
*TT*: Total testing time

#### 3.3.3.2 Inspection Metric

This metric is calculated by comparing the number of parts that have to be inspected against the ideal number of inspections. The number of parts that have to be inspected is calculated by subtracting the number of parts that are replaced from the total number of parts. The ideal number of inspections is equal to the theoretical minimum number of parts not requiring a replacement during refurbishing. Thus, the inspection metric is calculated as

$$\alpha_{\text{Inspection}} = \frac{INS}{TP - RP} \tag{3.12}$$

where

*INS*: Number of ideal inspections
*RP*: Number of replaced parts

### 3.3.4 Part Interfacing

In this category, there are two metrics: assembly metric and disassembly metric.

#### 3.3.4.1 Assembly Metric

The number of ideal parts, ideal assembly time per part (25 seconds), and total assembly time are used to calculate the assembly metric.

$$\alpha_{\text{Assembly}} = \frac{IP \cdot 25\,\text{s}}{AT} \tag{3.13}$$

where

*IP*: Number of ideal parts
*AT*: Total assembly time

#### 3.3.4.2 Disassembly Metric

The number of ideal parts, ideal disassembly time per part (15 seconds), and total disassembly time are used to calculate the disassembly metric.

$$\alpha_{\text{Disassembly}} = \frac{IP \cdot 15\,\text{s}}{DT} \tag{3.14}$$

where

*DT*: Total disassembly time

### 3.3.5 Construction of the Remanufacturability Index by Combining Metrics

The key part replacement metric is given more importance while constructing the remanufacturability index. It is considered as "level one" metric, while all the other metrics (known as "level two" metrics) are combined using the weighted, inverted addition technique. The resulting remanufacturability index is as follows:

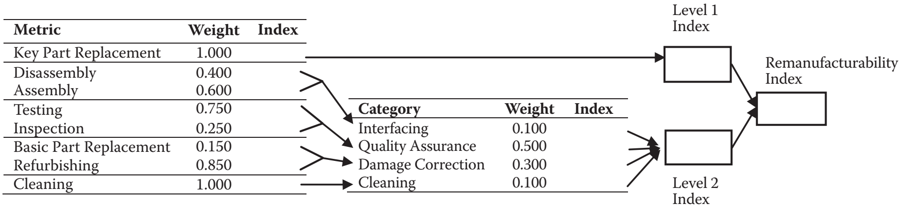
$$\alpha_{\text{Remanufacturability}} = \frac{\alpha_{Key\ replacement}}{\sum_{i=1}^{7} \frac{w_i}{\alpha_i}} \tag{3.15}$$

where $w_i$ is the weight associated with the *i*th "level two" metric.

We can summarize the process of obtaining the remanufacturability index as follows:

1. The values of each of the eight metrics are obtained using Equations (3.7) through (3.14).
2. Category Indices are calculated by combining the appropriate metrics using weighted inverted addition.
3. The second-level index is calculated by combining the category indices using the weighted inverted addition.
4. The remanufacturability index is calculated by multiplying the first-level (Key Part Replacement) and second-level indices.

Figure 3.3 presents a schematic representation of the remanufacturability metric calculation procedure.



| Metric | Weight | Index |
|---|---|---|
| Key Part Replacement | 1.000 | |
| Disassembly | 0.400 | |
| Assembly | 0.600 | |
| Testing | 0.750 | |
| Inspection | 0.250 | |
| Basic Part Replacement | 0.150 | |
| Refurbishing | 0.850 | |
| Cleaning | 1.000 | |

| Category | Weight | Index |
|---|---|---|
| Interfacing | 0.100 | |
| Quality Assurance | 0.500 | |
| Damage Correction | 0.300 | |
| Cleaning | 0.100 | |

**FIGURE 3.3**
Calculation of the remanufacturability index.

### 3.3.6 Case Example

In this section, we evaluate the remanufacturability of a personal computer (PC) design using the remanufacturability index. The data required for the calculation of various metrics are presented in Tables 3.6 through 3.9.

Figure 3.4 shows the calculation of remanufacturability index for the PC design. Weight and index values associated with each metric and category are also presented in this figure.

Category indices (*I*: Interfacing, *Q*: Quality assurance, *D*: Damage correction, and *C*: Cleaning) and remanufacturability index (*RI*) are calculated using the metric indices as follows:

$$I = \frac{1}{\dfrac{60\%}{\alpha_{Assembly}} + \dfrac{40\%}{\alpha_{Disassembly}}} = \frac{1}{\dfrac{60\%}{0.692} + \dfrac{40\%}{0.587}} = 0.646$$

$$Q = \frac{1}{\dfrac{75\%}{\alpha_{Testing}} + \dfrac{25\%}{\alpha_{Inspection}}} = \frac{1}{\dfrac{75\%}{0.931} + \dfrac{25\%}{0.800}} = 0.894$$

$$D = \frac{1}{\dfrac{85\%}{\alpha_{Refurbishing}} + \dfrac{15\%}{\alpha_{Basic\ Replacement}}} = \frac{1}{\dfrac{85\%}{0.412} + \dfrac{15\%}{0.765}} = 0.443$$

$$RI = \frac{\alpha_{key\ replacement}}{\dfrac{10\%}{I} + \dfrac{50\%}{Q} + \dfrac{30\%}{D} + \dfrac{10\%}{C}}$$

$$= \frac{1}{\dfrac{10\%}{0.646} + \dfrac{50\%}{0.894} + \dfrac{30\%}{0.443} + \dfrac{10\%}{0.529}} = 0.633$$

**TABLE 3.6**
Questionnaire for the Computer Design Considered in the Example

| | | Number of Parts | Large Relative Motions? | Different Material Properties Required? | Required to Facilitate Assembly or Disassembly? | Required to Isolate Wear? | Significant Intrinsic Value? | Does Part Fatigue? | Will Parts Require Adjustment? | Can Coating be Reapplied? | Can Worn Surfaces be Restored? | Can Damage be Refurbished? | Theoretical Minimum Number of Parts | Number of Refurbished Parts | Total Number of Replaced Parts | Number of Ideal Inspections | Number of Key Parts | Number of Key Parts Replaced |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **#** | **Part Name** | **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** | **K** | **L** | **M** | **N** | **O** | **P** | **Q** |
| 1 | Top cover | 1 | — | — | Y | N | N | N | — | — | — | Y | 1 | 1 | 0 | 1 | 0 | 0 |
| 2 | Floppy drive's cover face | 1 | — | — | Y | N | N | N | — | — | — | Y | 1 | 1 | 0 | 1 | 0 | 0 |
| 3 | Floppy disk drive | 1 | — | — | N | N | N | N | — | — | — | N | 0 | 0 | 1 | 0 | 0 | 0 |
| 4 | Hard drive's cover face | 1 | — | — | Y | N | N | N | — | — | — | Y | 1 | 1 | 0 | 1 | 0 | 0 |
| 5 | Hard Disk drive | 2 | Y | Y | N | N | Y | Y | Y | — | — | Y | 2 | 2 | 0 | 2 | 2 | 0 |
| 6 | Plastic back panel | 1 | — | — | Y | N | N | N | — | — | — | Y | 1 | 1 | 0 | 1 | 0 | 0 |
| 7 | Network card | 1 | — | — | N | N | N | N | — | — | — | N | 0 | 0 | 1 | 0 | 0 | 0 |
| 8 | Expansion card | 1 | — | — | N | N | N | N | — | — | — | N | 0 | 0 | 1 | 0 | 0 | 0 |
| 9 | RAM SIMMs (RSM) | 2 | — | — | N | N | Y | N | — | — | — | N | 0 | 0 | 0 | 0 | 2 | 0 |
| 10 | Key lock | 1 | — | — | N | N | N | N | — | — | — | Y | 0 | 1 | 0 | 0 | 0 | 0 |
| 11 | Power unit | 1 | — | — | N | N | Y | N | — | — | — | N | 0 | 0 | 0 | 0 | 1 | 0 |
| 12 | Plastic front panel | 1 | — | — | Y | N | N | N | — | — | — | Y | 1 | 1 | 0 | 1 | 0 | 0 |
| 13 | HDD and FDD stand | 1 | — | — | Y | N | N | N | — | — | — | Y | 1 | 1 | 0 | 1 | 0 | 0 |
| 14 | Motherboard | 1 | — | Y | N | N | Y | N | — | — | — | N | 1 | 0 | 0 | 0 | 1 | 0 |
| 15 | Power switch | 1 | — | — | N | N | N | N | — | — | — | Y | 0 | 1 | 0 | 0 | 0 | 0 |

It must be noted that a high remanufacturability index does not necessarily mean that the product should be remanufactured. It just indicates that the product is suitable for remanufacturing from the design point of view.

## 3.4 Fuzzy Cost–Benefit Function

In this section, we present a fuzzy cost–benefit function approach (Pochampally et al., 2003) for the evaluation of alternative product designs.

**TABLE 3.7**

Calculation of Disassembly, Reassembly Times Together with the Cleaning Score

| | | Number of Parts | If Part can Corrode-is Part Protectively Coated | Manual Removal Time Per Part | Manual Handling Time Per Part | Disassembly Time (Seconds) (A*F(B)*[C+D]) | Manual Handling Time Per Part | Manual Insertion Time Per Part | Operating Time (Seconds) | Cleaning Code | Cleaning Score Per Part | Total Cleaning Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **#** | **Part Name** | **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** | **K** |
| 1 | Top cover | 1 | — | 20 | 5 | 25 | 5 | 25 | 30 | A | 1 | 1 |
| 2 | Floppy drive's cover face | 1 | — | 10 | 5 | 15 | 5 | 20 | 25 | A | 1 | 1 |
| 3 | Floppy disk drive | 1 | — | 10 | 5 | 15 | 5 | 20 | 25 | A | 1 | 1 |
| 4 | Hard drive's cover face | 1 | — | 10 | 5 | 15 | 5 | 20 | 25 | A | 1 | 1 |
| 5 | Hard disk drive | 2 | — | 15 | 5 | 20 | 5 | 25 | 30 | A | 1 | 2 |
| 6 | Plastic back panel | 1 | — | 10 | 5 | 15 | 5 | 15 | 20 | A | 1 | 1 |
| 7 | Network card | 1 | — | 10 | 5 | 15 | 5 | 15 | 20 | A | 1 | 1 |
| 8 | Expansion card | 1 | — | 10 | 5 | 15 | 5 | 15 | 20 | A | 1 | 1 |
| 9 | RAM SIMMs (RSM) | 2 | — | 5 | 5 | 10 | 5 | 10 | 15 | A | 1 | 2 |
| 10 | Key lock | 1 | — | 5 | 5 | 10 | 5 | 10 | 15 | A | 1 | 1 |
| 11 | Power unit | 1 | — | 10 | 5 | 15 | 5 | 15 | 20 | A | 1 | 1 |
| 12 | Plastic front panel | 1 | — | 10 | 5 | 15 | 5 | 15 | 20 | A | 1 | 1 |
| 13 | HDD and FDD stand | 1 | — | 10 | 5 | 15 | 5 | 15 | 20 | A | 1 | 1 |
| 14 | Motherboard | 1 | — | 15 | 5 | 20 | 5 | 20 | 25 | A | 1 | 1 |
| 15 | Power switch | 1 | — | 5 | 5 | 10 | 5 | 10 | 15 | A | 1 | 1 |
| | | | | | TOTAL | 230 | | TOTAL | 325 | | TOTAL | 17 |

### 3.4.1 Construction and Components of the Fuzzy Cost–Benefit Function

The fuzzy cost–benefit function (*FCBF*) associated with the design alternative $x$ of interest is calculated by considering the equivalent values (*EV*) of nine terms as follows:

$$FCBF_x = \frac{\text{EV of } (NPSR_x + RUR_x + RR_x)}{\text{EV of } (PC_x + CC_x + RCP_x + DC_x + LSC_x + INVC_x)} \tag{3.16}$$

**TABLE 3.8**

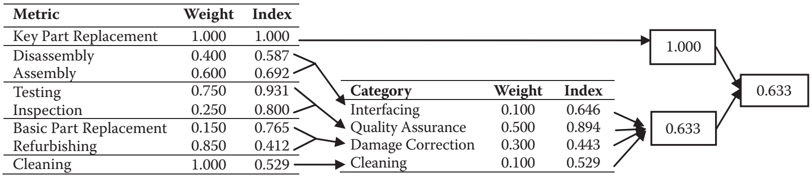
Calculation of Testing Times

| | Number of Times Test Performed | Handling Time Required | Testing Time Required (Seconds) | Total Testing Time (Seconds) |
|---|---|---|---|---|
| **Tested Component** | **A** | **B** | **C** | **D** |
| Floppy disk drive | 1 | 60 | 60 | 120 |
| Hard disk drive | 2 | 60 | 300 | 720 |
| Network card | 1 | 30 | 60 | 90 |
| Expansion card | 1 | 30 | 60 | 90 |
| Ram SIMMs | 2 | 30 | 60 | 180 |
| Power unit | 1 | 60 | 120 | 180 |
| Motherboard | 1 | 60 | 300 | 360 |
| | | | TOTAL | 1740 |

**TABLE 3.9**

Summary of the Data Required for Metric Calculation

| | |
|---|---|
| Total number of parts | 17 |
| Number of ideal parts | 9 |
| Number of parts requiring refurbishing | 10 |
| Total number of replaced parts | 7 |
| Number of key parts | 6 |
| Number of key parts replaced | 3 |
| Total number of tests | 9 |
| Number of ideal inspections | 8 |
| Cleaning score | 17 |
| Total disassembly time (seconds) | 230 |
| Total assembly time (seconds) | 325 |
| Total test time (seconds) | 1740 |



| Metric | Weight | Index |
|---|---|---|
| Key Part Replacement | 1.000 | 1.000 |
| Disassembly | 0.400 | 0.587 |
| Assembly | 0.600 | 0.692 |
| Testing | 0.750 | 0.931 |
| Inspection | 0.250 | 0.800 |
| Basic Part Replacement | 0.150 | 0.765 |
| Refurbishing | 0.850 | 0.412 |
| Cleaning | 1.000 | 0.529 |

| Category | Weight | Index |
|---|---|---|
| Interfacing | 0.100 | 0.646 |
| Quality Assurance | 0.500 | 0.894 |
| Damage Correction | 0.300 | 0.443 |
| Cleaning | 0.100 | 0.529 |

**FIGURE 3.4**
Calculating the remanufacturability index for a PC design.

where $NPSR_x$ is the total new product sale revenue of design alternative $x$ per period, $RUR_x$ is the total reuse revenue of design alternative $x$ per period, $RR_x$ is the total recycling revenue of used products designed according to design alternative $x$ per period, $PC_x$ is the total production cost of new products designed according to design alternative $x$ per period, $CC_x$ is the total collection cost of used products designed according to design alternative $x$ per period, $RCP_x$ is the total reprocessing cost of used products designed according to design alternative $x$ per period, $DC_x$ is the total disposal cost of used products designed according to design alternative $x$, $LSC_x$ is the loss-of-sale cost of design alternative $x$, and $INVC_x$ is the investment cost of design alternative $x$. The following subsections present explanations for the calculation of the terms involved in the *FCBF* expression.

### *3.4.1.1 Total New Product Sale Revenue per Period (NPSR)*

This revenue is influenced by the demand for new products per period ($\boldsymbol{D}_x$) and the selling price of each new product ($P_x$). It can be expressed as follows:

$$NPSR_x = D_x \cdot P_x \tag{3.17}$$

### *3.4.1.2 Total Reuse Revenue per Period (RUR)*

The *RUR* of design alternative $x$ is affected by the fuzzy supply of the product per period ($SUP_x$) and a number of other factors associated with the components of each type $j$ in the product, including the resale value ($RV_{xj}$), multiplicity ($M_{xj}$), the fuzzy probability of missing ($pm_{xj}$), and the fuzzy probability of bad quality ($pb_{xj}$). The expression for this revenue can be written as follows:

$$RUR_x = \sum_j SUP_x \cdot RV_{xj} \cdot M_{xj} \cdot (1 - pb_{xj} - pm_{xj}) \tag{3.18}$$

### *3.4.1.3 Total Recycle Revenue per Period (RR)*

The number of components recycled per period is multiplied by the component recycling revenue factors in order to calculate the *RR* of design alternative $x$. The expression for this revenue can be written as follows:

$$RR_x = \sum_j [SUP_x \cdot RI_{xj} \cdot W_{xj} \cdot PRC_{xj} \cdot \{M_{xj} \cdot (1 - pm_{xj}) - M_{xj} \cdot (1 - pb_{xj} - pm_{xj})\}] \cdot F_{rr} \tag{3.19}$$

where $RI_{xj}$ is the recycling revenue index of component $j$ in design alternative $x$ (0 = lowest, 10 highest), $W_{xj}$ is the weight of component $j$ in design alternative $x$, $PRC_{xj}$ is the percentage of recyclable contents by weight in component $j$ of design alternative $x$, and $F_{rr}$ is the recycling revenue factor.

### 3.4.1.4 Total New Product Production Cost per Period (PC)

The demand for new products is multiplied by the cost to produce one new product ($C_x$) while calculating the $PC$ of products designed according to design alternative $x$ as follows:

$$PC_x = D_x \cdot C_x \tag{3.20}$$

### 3.4.1.5 Total Collection Cost per Period (CC)

Total collection cost associated with the used products designed according to design alternative $x$ is calculated by multiplying the cost of collecting one used product ($COP_x$) by the supply of used products per period ($SUP_x$).

$$CC_x = SUP_x \cdot COP_x \tag{3.21}$$

### 3.4.1.6 Total Reprocessing Cost per Period (RC)

This cost is influenced by the supply of used products per period, disassembly time of the root node of the product ($T(Root_x)$), disassembly time of each subassembly in the product ($T(S_{xk})$), and the reprocessing cost per unit time ($RC$). It can be written as follows:

$$RCP_x = SUP_x \cdot \;\; T(Root_x) + \sum_{k=1}^{L_x} T(S_{xk}) \;\; \cdot RC \tag{3.22}$$

where $L_x$ is number of subassemblies in design alternative $x$.

### 3.4.1.7 Total Disposal Cost per Period (DC)

Total disposal cost associated with the used products designed according to design alternative $x$ is calculated by multiplying the component disposal cost by the number of component units disposed per period as follows:

$$DC_x = \sum_j [SUP_x \cdot DCI_{xj} \cdot W_{xj} \cdot (1 - PRC_{xj}) \cdot \{M_{xj} \cdot (1 - pm_{xj}) - M_{xj} \cdot (1 - pb_j - pm_{xj})\}] \cdot F_{dc} \tag{3.23}$$

where $DCI_{xj}$ is the disposal cost index of component $j$ in design alternative $x$ (0 = lowest, 10 = highest), and $F_{dc}$ is the disposal cost factor.

#### *3.4.1.8 Loss of Sale Cost per Period (LC)*

This cost occurs if the demand for products designed according to design alternative $x$ cannot be met in a timely manner mainly due to the highly uncertain supply of used products. $LC$ is usually expressed as a fuzzy number since it is usually predicted by experts.

#### *3.4.1.9 Investment Cost (INVC)*

The capital required to acquire the facilities and machinery for the production of new products as well as collection and reprocessing of used products can be considered as investment cost. It can be fuzzy or crisp depending on the available product- and facilities-related data.

### 3.4.2 Procedure

1. Any design alternative with an FCBF value of less than 1 is eliminated.
2. The design alternative with the lowest INVC is assigned as the defender, while the challenger is the design alternative with the next-lowest INVC.
3. The ratio of the EV of incremental total revenue ΔBZ (between the challenger and the defender) to the EV of incremental total cost ΔCZ (between the challenger and the defender) is calculated. The defender is eliminated if this ratio is more than 1. Otherwise, the challenger is eliminated.
4. Steps 2 and 3 are repeated until there is only one design alternative (the most economical design alternative) left in the set.

### 3.4.3 Example

Figures 3.5 through 3.7 present the structures of three design alternatives considered in this example. Various characteristics of these alternatives are given in Table 3.10. Tables 3.11 through 3.13 present the component characteristics for design alternatives 1 through 3, respectively. In addition, the following data are used:

$$T(Root_1) = 4\text{ min}, T(Root_2) = 2\text{ min}, T(Root_3) = 2.5\text{ min}, T(S_{11}) = 7\text{ min},$$

$$T(S_{12}) = 4\text{ min}, T(S_{21}) = 5\text{ min}, T(S_{31}) = 7\text{ min}, T(S_{32}) = 7\text{ min},$$

$$F_{rr} = 0.3\ \$/\text{lb}, F_{dc} = 0.15\ \$/\text{lb}, RC = 0.60\ \$/\text{min}.$$

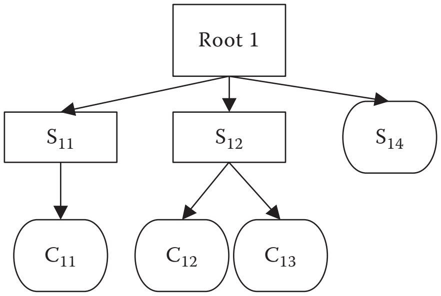


**FIGURE 3.5**
Subassemblies and components of design alternative 1.

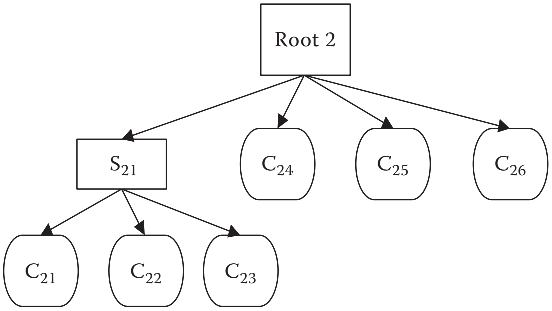


**FIGURE 3.6**
Subassemblies and components of design alternative 2.

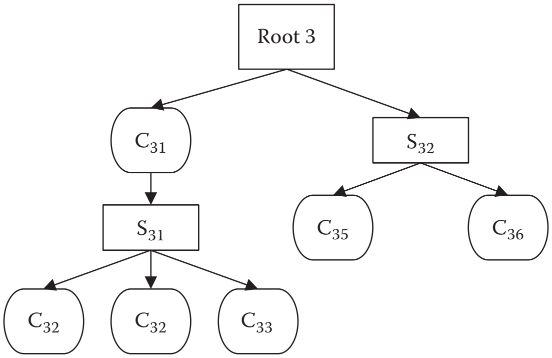


**FIGURE 3.7**
Subassemblies and components of design alternative 3.

**TABLE 3.10**

Characteristics of Design Alternatives

| Design alternative | *SUP* | *COP* | *INVC* | *D* | *P* | *C* | *LSC* |
|---|---|---|---|---|---|---|---|
| 1 | (180,200,220) | 25 | 20000 | 1000 | 100 | 20 | (200,400,600) |
| 2 | (200,230,250) | 22 | 20000 | 1000 | 35 | 20 | (100,200,300) |
| 3 | (400,500,600) | 30 | 25000 | 700 | 90 | 15 | (300,400,500) |

**TABLE 3.11**

Component Characteristics for Design Alternative 1

| Component | $RV_{1j}$ | $M_{1j}$ | $W_{1j}$ | $RI_{1j}$ | $PRC_{1j}$ | $DCI_{1j}$ | $pb_{1j}$ | $pm_{1j}$ |
|---|---|---|---|---|---|---|---|---|
| $C_{11}$ | 4.0 | 1 | 3.2 | 1 | 70% | 6 | (0.1,0.2,0.3) | (0.2,0.3,0.4) |
| $C_{12}$ | 3.5 | 2 | 1.5 | 3 | 65% | 4 | (0.3,0.4,0.5) | (0.1,0.1,0.2) |
| $C_{13}$ | 2.0 | 3 | 2.8 | 2 | 80% | 5 | (0.3,0.4,0.5) | (0.2,0.2,0.3) |
| $C_{14}$ | 5.0 | 2 | 4.0 | 9 | 50% | 3 | (0.4,0.5,0.6) | (0.1,0.2,0.2) |

**TABLE 3.12**

Component Characteristics for Design Alternative 2

| Component | $RV_{2j}$ | $M_{2j}$ | $W_{2j}$ | $RI_{2j}$ | $PRC_{2j}$ | $DCI_{2j}$ | $pb_{2j}$ | $pm_{2j}$ |
|---|---|---|---|---|---|---|---|---|
| $C_{21}$ | 6.0 | 2 | 2.9 | 2 | 90% | 4 | (0.3,0.4,0.5) | (0.0,0.0,0.0) |
| $C_{22}$ | 5.0 | 2 | 1.4 | 2 | 60% | 5 | (0.5,0.6,0.7) | (0.0,0.0,0.0) |
| $C_{23}$ | 7.0 | 1 | 3.4 | 5 | 40% | 2 | (0.4,0.5,0.6) | (0.1,0.2,0.3) |
| $C_{24}$ | 4.5 | 3 | 1.8 | 3 | 20% | 3 | (0.2,0.3,0.4) | (0.0,0.1,0.1) |
| $C_{25}$ | 2.0 | 4 | 3.5 | 4 | 50% | 6 | (0.4,0.5,0.6) | (0.2,0.2,0.3) |
| $C_{26}$ | 5.0 | 2 | 4.0 | 6 | 80% | 1 | (0.1,0.2,0.3) | (0.1,0.1,0.2) |

**TABLE 3.13**

Component Characteristics for Design Alternative 3

| Component | $RV_{3j}$ | $M_{3j}$ | $W_{3j}$ | $RI_{3j}$ | $PRC_{3j}$ | $DCI_{3j}$ | $pb_{3j}$ | $pm_{3j}$ |
|---|---|---|---|---|---|---|---|---|
| $C_{31}$ | 1.0 | 2 | 5.2 | 8 | 40% | 2 | (0.1,0.2,0.2) | (0.1,0.1,0.2) |
| $C_{32}$ | 6.0 | 3 | 3.8 | 7 | 50% | 5 | (0.2,0.3,0.3) | (0.0,0.0,0.0) |
| $C_{33}$ | 3.0 | 2 | 2.6 | 6 | 30% | 7 | (0.3,0.4,0.5) | (0.1,0.1,0.2) |
| $C_{34}$ | 2.0 | 4 | 2.9 | 2 | 80% | 2 | (0.4,0.5,0.6) | (0.1,0.2,0.3) |
| $C_{35}$ | 2.0 | 2 | 1.8 | 3 | 70% | 4 | (0.1,0.2,0.2) | (0.1,0.1,0.2) |
| $C_{36}$ | 2.9 | 1 | 4.5 | 1 | 60% | 5 | (0.4,0.5,0.6) | (0.1,0.2,0.3) |

Based on the foregoing data, the fuzzy cost–benefit function values for design alternatives 1 through 3 are calculated as $FCB_1 = (2.09, 2.18, 2.27)$, $FCB_2 = (0.83, 0.94, 1.06)$, and $FCB_3 = (1.21, 1.37, 1.67)$. Upon defuzzification (Equation 2.14), we get the following defuzzified numbers: $FCB_1 = 2.18$, $FCB_2 = 0.94$, and $FCB_3 = 1.42$. Design alternative 2 is eliminated since $FCB_2$ is less than 1. Design alternative 1 is considered as defender, and design alternative 3 is considered as challenger since $INVC_3$ is larger than $INVC_1$. The defuzzified ratio of $EV$ of $\Delta BZ$ to $EV$ of $\Delta CZ$ is calculated as 3.96. Since this value is greater than 1, the defender (design alternative 1) is eliminated. Hence, design alternative 3 is the most economical product design.

## 3.5 Use of House of Quality

House of quality (HOQ) is generally used in the development of new products. However, it is also useful while evaluating the remanufacturability potential of an existing product design. In the first case, the customer is the end user who will use the new product. In the latter case, the customer is the independent remanufacturer or the original equipment manufacturer (OEM) who remanufactures its own product.

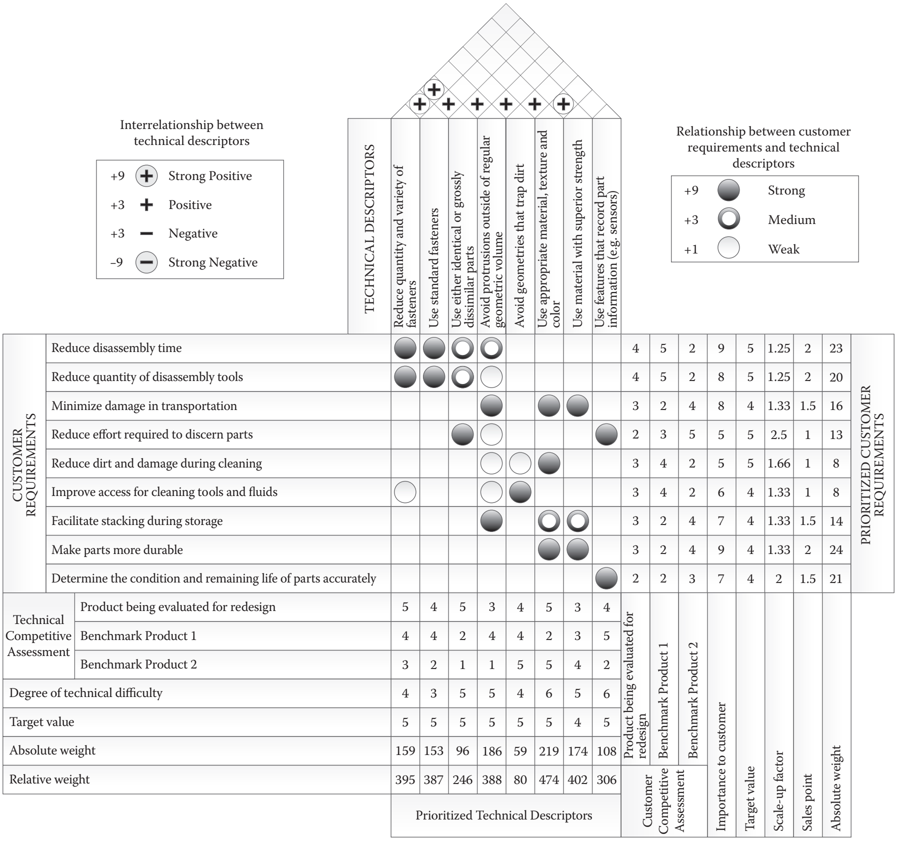
We illustrate the application of HOQ for remanufacturability assessment by developing an HOQ for an existing product design. The resulting HOQ can be seen in Figure 3.8. In the customer requirements section of the HOQ, we list some of the features that will ease the remanufacturing process of the product. Technical descriptors involve design tips that can be used to satisfy the customer requirements listed in the customer requirements section. The numbers in the center of the house represent the relationships between customer requirements and design tips.

For each customer requirement, a competitive assessment is made by comparing the product being evaluated with the other two products produced by the competitors. Based on this assessment, target value and scale-up factor are determined. After determining "importance to customer" and "sales point," the absolute weight is calculated (see Equation (2.24)). For instance, the absolute weight for the second customer requirement can be calculated as follows:

$$\text{Absolute weight} = 8 \cdot 1.25 \cdot 2 = 20 .$$

For each technical descriptor, a competitive assessment is made by comparing the product being evaluated with the other two products produced by the competitors. Based on this assessment, the target value is determined for each technical descriptor. The absolute weight is calculated using Equation (2.25) for each technical descriptor. For instance, the absolute weight for the fourth technical descriptor can be calculated as follows:

$$a_4 = 3 \cdot 9 + 1 \cdot 8 + 9 \cdot 8 + 1 \cdot 5 + 1 \cdot 5 + 1 \cdot 6 + 9 \cdot 7 = 186$$



Interrelationship between technical descriptors

| | | |
|---|---|---|
| +9 | ⊕ | Strong Positive |
| +3 | + | Positive |
| +3 | − | Negative |
| −9 | ⊖ | Strong Negative |

Relationship between customer requirements and technical descriptors

| | | |
|---|---|---|
| +9 | ● | Strong |
| +3 | ◎ | Medium |
| +1 | ○ | Weak |

| CUSTOMER REQUIREMENTS | Reduce quantity and variety of fasteners | Use standard fasteners | Use either identical or grossly dissimilar parts | Avoid protrusions outside of regular geometric volume | Avoid geometries that trap dirt | Use appropriate material, texture and color | Use material with superior strength | Use features that record part information (e.g. sensors) | Product being evaluated for redesign | Benchmark Product 1 | Benchmark Product 2 | Importance to customer | Target value | Scale-up factor | Sales point | Absolute weight |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Reduce disassembly time | ● | ● | ◎ | ◎ | | | | | 4 | 5 | 2 | 9 | 5 | 1.25 | 2 | 23 |
| Reduce quantity of disassembly tools | ● | ● | ◎ | ○ | | | | | 4 | 5 | 2 | 8 | 5 | 1.25 | 2 | 20 |
| Minimize damage in transportation | | | | ● | | ● | ● | | 3 | 2 | 4 | 8 | 4 | 1.33 | 1.5 | 16 |
| Reduce effort required to discern parts | | | ● | ○ | | | | ● | 2 | 3 | 5 | 5 | 5 | 2.5 | 1 | 13 |
| Reduce dirt and damage during cleaning | | | | ○ | ○ | ● | | | 3 | 4 | 2 | 5 | 5 | 1.66 | 1 | 8 |
| Improve access for cleaning tools and fluids | ○ | | | ○ | ● | | | | 3 | 4 | 2 | 6 | 4 | 1.33 | 1 | 8 |
| Facilitate stacking during storage | | | | ● | | ◎ | ◎ | | 3 | 2 | 4 | 7 | 4 | 1.33 | 1.5 | 14 |
| Make parts more durable | | | | | | ● | ● | | 3 | 2 | 4 | 9 | 4 | 1.33 | 2 | 24 |
| Determine the condition and remaining life of parts accurately | | | | | | | | ● | 2 | 2 | 3 | 7 | 4 | 2 | 1.5 | 21 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Technical Competitive Assessment: Product being evaluated for redesign | 5 | 4 | 5 | 3 | 4 | 5 | 3 | 4 |
| Technical Competitive Assessment: Benchmark Product 1 | 4 | 4 | 2 | 4 | 4 | 2 | 3 | 5 |
| Technical Competitive Assessment: Benchmark Product 2 | 3 | 2 | 1 | 1 | 5 | 5 | 4 | 2 |
| Degree of technical difficulty | 4 | 3 | 5 | 5 | 4 | 6 | 5 | 6 |
| Target value | 5 | 5 | 5 | 5 | 5 | 5 | 4 | 5 |
| Absolute weight | 159 | 153 | 96 | 186 | 59 | 219 | 174 | 108 |
| Relative weight | 395 | 387 | 246 | 388 | 80 | 474 | 402 | 306 |

**FIGURE 3.8**
Completed house of quality for evaluating the remanufacturability of a product.

The relative weight for each technical descriptor is calculated using Equation (2.26). For instance, the relative weight for the fourth technical descriptor can be calculated as follows:

$$b_4 = 3 \cdot 23 + 1 \cdot 20 + 9 \cdot 16 + 1 \cdot 13 + 1 \cdot 8 + 1 \cdot 8 + 9 \cdot 14 = 388$$

By looking at the absolute and relative weight values presented in Figure 3.8, we can state that the most important technical descriptor is "use of appropriate material, texture and color." This descriptor is followed by "avoiding protrusions outside of regular geometric volume," and so on. Remanufacturability of product design can be improved by concentrating engineering efforts on one or more of these technical descriptors. While making decisions, the degree of technical difficulty associated with a technical descriptor should also be considered besides its absolute and relative weight values.

## 3.6 Other Models

There are several other models dealing with remanufacturing-related product design issues. Shu and Flowers (1999) compare remanufacturing costs against other life-cycle costs (e.g., manufacturing, maintenance) for alternative joint designs. They assert that design features facilitating assembly and recycling can have negative impacts on the remanufacturability of a product. Zwolinski et al. (2006) developed a design for a remanufacturing tool called REPRO$^2$ that can make comparisons between the product under consideration and the different product profiles by using a database involving 11 remanufactured product profiles and various rules. Based on the workshops undertaken in two UK universities, Ijomah et al. (2007) discuss some product features and characteristics required for the successful remanufacturing of products. Yuksel (2010) uses Quality Function Deployment (QFD) to investigate automobile engine characteristics that will ease remanufacturing.

## 3.7 Conclusions

In this chapter, four models were presented to illustrate the main product design issues in remanufacturing. The first model proposed an index to evaluate alternative product designs based on the disassembly process. In the second model, a metric was developed to assess the remanufacturability of a product considering its design features. A fuzzy cost–benefit function was presented in the third model. The fourth model illustrated the use of HOQ in the remanufacturability analysis of a product design. The previous section provided a review of other models developed for the evaluation of products considering remanufacturing-related design characteristics.

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# 4

# *Reverse and Closed-Loop Supply Chain Design*

## 4.1 The Issue

In traditional manufacturing, manufacturers establish supply chains to obtain required manufacturing resources (raw material, components, etc.) as well as to distribute finished products to their customers. In remanufacturing, the need for the collection of used products from customers requires the construction of reverse supply chains in addition to forward supply chains. A reverse supply chain involves all the activities associated with the collection and either recovery (remanufacturing or recycling) or disposal of used products. In a reverse supply chain designed for remanufacturing, there are at least three parties:

- Collection centers where customers return used products
- Remanufacturing facilities
- Demand centers where customers buy remanufactured products

A manufacturer dealing with remanufacturing activities has to administer its reverse supply chain together with its forward supply chain. The combination of forward and reverse supply chains is called a closed-loop supply chain.

In this chapter we analyze various issues associated with the design of reverse and closed-loop supply chains involving the determination of the number of units of used products of each type to be picked for remanufacturing, identification of efficient production facilities, and achievement of the optimal transfer of goods across a closed-loop supply chain. Three models are presented to address these issues. The first model uses goal programming, while linear integer and linear physical programming are employed by the second and third models, respectively.

## 4.2 First Model (Goal Programming)

In this section we present a unified approach to addressing a network design issue in remanufacturing using goal programming (GP). Section 4.2.1 presents the goal programming model, and Section 4.2.2 presents its application to a numerical example.

### 4.2.1 Goal Programming Model

In this section, we formulate a single-period trans-shipment model that (a) determines the number of units of used product of each type to be picked for remanufacturing, (b) identifies the efficient production facilities, and (c) achieves the optimal transfer of goods across a closed-loop supply chain, in one unified solution. The goods consist of used products from the collection centers to the production facilities as well as remanufactured and newly manufactured products from the production facilities to the demand centers.

We assume that the inventory cost of a used product and a remanufactured product is 20% of its collection and remanufacturing cost, respectively, and that of a newly produced product is 25% of its production cost. We consider three goals in our GP model:

1. Maximize the total profit in the closed-loop supply chain (*TPR*)
2. Maximize the revenue from recycling (*RRC*)
3. Minimize the number of disposed items (*NDI*)

The first two goals involve minimizing the negative deviation from the respective target values, while the third goal, which has an "environmentally benign" character rather than a financial motive, involves minimizing the positive deviation from the target value. The cost and revenue criteria and the system constraints considered in our model include the following:

#### *4.2.1.1 Revenues*

- *Reuse Revenue*

$$\sum_{p}\sum_{i}\{Y_{pi}\cdot RSL_{p}\} \tag{4.1}$$

where $Y_{pi}$ is the decision variable representing the number of units of product type $p$ picked for remanufacturing at collection center $i$, and $RSL_p$ is the total resale revenue of product $p$.

- *Recycling Revenue*

$$\sum_{p}\sum_{i}\{(SUP_{pi}-Y_{pi})\cdot IRR_{P}\cdot WGT_{p}\cdot RCP_{p}\cdot RCYC_{p}\} \tag{4.2}$$

where $SUP_{pi}$ is the supply of used product $p$ at collection center $i$, $IRR_p$ is the recycling revenue index of product $p$, $WGT_p$ is the weight of product $p$, $RCP_p$ is the percentage of recyclable contents by weight in product $p$, and $RCYC_p$ is the total recycling revenue of product $p$.

- *New Product Sales Revenue*

$$\sum_{p}\sum_{m}\sum_{k} PS_{p}\cdot NP_{pmk} \tag{4.3}$$

where $PS_p$ is the selling price of a unit of new product of type $p$, and $NP_{pmk}$ is the decision variable representing the number of new product type $p$ transported from production facility $m$ to demand center $k$.

### 4.2.1.2 Costs

- *Collection/Retrieval Cost*

$$\sum_{i}\sum_{p} C_{i}\cdot SUP_{pi} \tag{4.4}$$

where $C_i$ is the cost per product retrieved at collection center $i$.

- *Processing Cost*

This cost can be determined by summing the disassembly cost of used products, remanufacturing cost of used products, and production cost of new products:

$$DISC\cdot\sum_{p}\sum_{i}\sum_{m} DIST_{p}\cdot E_{pim} + \sum_{p}\sum_{i}\sum_{m} RC_{m}\cdot F_{pmk} + \sum_{p}\sum_{m}\sum_{k} NPC_{m}\cdot NP_{pmk} \tag{4.5}$$

where $DISC$ is the disassembly cost per unit time, $DIST_p$ is the disassembly time for product $p$, $E_{pim}$ is the decision variable representing the number of used products of type $p$ transported from collection center $i$ to remanufacturing facility $m$, $RC_m$ is the cost to remanufacture at production facility $m$, $F_{pmk}$ is the decision variable representing the number of used products of type $p$ transported from production facility $m$ to demand center $k$, and

$NPC_m$ is the cost to produce one unit of new product at production facility $m$.

- *Inventory Cost*

This cost can be determined by summing the carrying cost of used products inventory at the collection center, the carrying cost of remanufactured products inventory at the production facility, and the carrying cost of newly manufactured products inventory at the production facility.

$$\sum_p \sum_i \sum_m \left(C_i/5\right)\cdot E_{pim} + \sum_p \sum_m \sum_k \{(RC_m/4)\cdot E_{pmk} + (NPC_m/4)\cdot NP_{pmk}\} \qquad (4.6)$$

- *Transportation Costs*

This cost can be determined by summing the cost associated with the transportation of used products from collection centers to the production facilities and the cost associated with the transportation of remanufactured and new products from the production facilities to demand centers.

$$TC_{im}\cdot \sum_p \sum_i \sum_m E_{pim} + TR_{mk}\cdot \sum_p \sum_m \sum_k \left(E_{pmk} + NP_{pmk}\right) \qquad (4.7)$$

where $TC_{im}$ is the cost to transport one unit from collection center $i$ to the remanufacturing facility $m$, and $TR_{mk}$ is the cost to transport one unit from the remanufacturing facility $m$ to the demand center $k$.

- *Disposal Cost*

Disposal cost depends on the number of units disposed, cost of disposing a product, percentage of recyclable content in the product, and the disposal cost index (a number on a scale 0–10, the higher the number, the more difficult or expensive it is to dispose of the product).

$$\sum_p \sum_i \{(SUP_{pi} - Y_{pi})\cdot ID_p \cdot WGT_p \cdot (1 - RCP_p)\}\cdot DC_p \qquad (4.8)$$

where $ID_p$ is the disposal cost index of product $p$ (0 = lowest, 10 = highest), and $DC_p$ is the disposal cost of product $p$.

#### 4.2.1.3 System Constraints

- The number of used products sent to all production facilities from a collection center *i* must be equal to the number of used products picked for remanufacturing at that collection center.

$$\sum_m E_{pim} = Y_{pi} \tag{4.9}$$

- Each demand center must be fully satisfied using new or remanufactured products.

$$\sum_m (F_{pmk} + NP_{pmk}) = D_{pk} \;\; \forall k \tag{4.10}$$

where $D_{pk}$ is the net demand for product type $p$ (remanufactured or new) at demand center $k$

- There is no loss of products in the supply chain due to reasons other than common cause variations, which cannot be prevented. A factor ($\psi_m$) is employed in order to address the unassignable (common) causes of variation at the production facility $m$.

$$\sum_k F_{pmk} = \sum_i E_{pim} \cdot \psi_m \;\; \forall m \tag{4.11}$$

- The total number of used products of type $p$ picked for remanufacturing at collection center $i$ cannot be greater than the total number of used products fit for remanufacturing.

$$Y_{pi} \le SUP_{pi} \cdot (1 - br_p) \tag{4.12}$$

where $br_p$ is probability of breakage of product $p$.

- The total number of used products of any type collected at all collection centers (before adjusting for the breakage probability) must be equal to or greater than the net demand.

$$\sum_p \sum_i SUP_{pi} \ge \sum_p \sum_k D_{pk} \tag{4.13}$$

- In order to prevent excess remanufactured products, remanufactured product quantity cannot be greater than the net demand.

$$\sum_p \sum_i Y_{pi} \le \sum_p \sum_k D_{pk} \tag{4.14}$$

- Used products' space usage at a production facility cannot be greater than the space available for used-product storage at that facility.

$$s_1 \cdot \sum_p \sum_i E_{pim} \le SC_{1m} \cdot V_m \tag{4.15}$$

where $s_1$ is the space occupied by 1 unit of used product (square units per product), $SC_{1m}$ is the storage capacity of remanufacturing facility $m$ for remanufactured and new products, and $V_m$ is the decision variable signifying the selection of production facility $m$ (1 if selected, 0 if not).

- New and remanufactured products' space usage at a production facility cannot be greater than the space available for new and remanufactured products at that production facility (assuming that the same space is used to store new and remanufactured products).

$$\sum_p \sum_k s_2 \cdot (F_{pmk} + NP_{pmk}) \le SC_{2m} \cdot V_m \tag{4.16}$$

where $s_2$ is the space occupied by 1 unit of remanufactured or new product (square units per product), and $SC_{2m}$ is the storage capacity of remanufacturing facility $m$ for used products

- Used products' space usage at a collection center cannot be greater than the space available for used products at that collection center.

$$s_1 \cdot \sum_p \sum_m E_{pim} \le SC_i \tag{4.17}$$

where $SC_i$ is the storage capacity of collection center $i$.

- A production facility can be considered "potential" if the ratio of throughput to the supply of used products of that production facility is equal to or greater than a preset potential value (this is valid only for remanufactured products).

$$(TPT_m / SUPRE_m) \cdot V_m \ge MTS \tag{4.18}$$

where $MTS$ is the minimum throughput per supply, $TPT_m$ is the throughput (considering only remanufactured products) of production facility $m$, and $SUPRE_m$ is the supply of used products at production facility $m$, different from $SUP_{pi}$, these are products that are fit for remanufacturing, after accounting for recycled, disposed, and new products.

- Nonnegativity Constraints

$$E_{pim}, F_{pmk}, NP_{pmk}, Y_{pi} \geq 0, \forall\, i, m, k, p \tag{4.19}$$

$$V_m \in [0,1]\, \forall\, m, 0 \text{ if facility } m \text{ not selected,1 if selected} \tag{4.20}$$

### 4.2.2 Numerical Example

We consider a closed-loop supply chain with three collection centers (1, 2, and 3), two production facilities to choose from (1 and 2), two demand centers to be served (1 and 2), and three types of products to pick from (1, 2, and 3). The data for the example are as follows:

> $C_i = 0.02$; $SUP_{11} = 60$; $SUP_{12} = 50$; $SUP_{13} = 30$; $SUP_{21} = 40$; $SUP_{22} = 50$; $SUP_{23} = 35$; $SUP_{31} = 40$; $SUP_{32} = 20$; $SUP_{33} = 35$; $DISC = 0.04$; $DIST_1 = 9$; $DIST_2 = 11$; $DIST_3 = 10$; $RC_1 = 10$; $RC_2 = 8$; $NPC_1 = 40$; $NPC_2 = 60$; $TC_{11} = 0.01$; $TC_{12} = 0.09$; $TC_{21} = 0.5$; $TC_{22} = 0.1$; $TC_{31} = 0.02$; $TC_{32} = 0.04$; $TR_{11} = 0.02$; $TR_{12} = 0.1$; $TR_{21} = 0.2$; $TR_{22} = 0.02$; $ID_1 = 3$; $ID_2 = 4$; $ID_3 = 4$; $WGT_1 = 0.7$; $WGT_2 = 0.8$; $WGT_3 = 0.7$; $RCP_1 = 0.6$; $RCP_2 = 0.4$; $RCP_3 = 0.8$; $DC_1 = 0.4$; $DC_2 = 0.2$; $DC_3 = 0.4$; $RSL_1 = 25$; $RSL_2 = 45$; $RSL_3 = 50$; $RCYC_1 = 3$; $RCYC_2 = 3$; $RCYC_3 = 2.5$; $IRR_1 = 5$; $IRR_2 = 3$; $IRR_3 = 3$; $PS_1 = 65$; $PS_2 = 53$; $PS_3 = 60$; $D_{11} = 25$; $D_{12} = 20$; $D_{21} = 20$; $D_{22} = 20$; $D_{31} = 20$; $D_{32} = 25$; $\psi_1 = 0.8$; $\psi_2 = 0.75$; $br_1 = 0.2$; $br_2 = 0.4$; $br_3 = 0.3$; $s_1 = 0.8$; $SC_{11} = 450$; $SC_{12} = 450$; $SC_1 = 200$; $SC_2 = 200$; $SC_3 = 200$; $s_2 = 0.8$; $SC_{21} = 550$; $SC_{22} = 550$; $MTS = 0.35$.

Upon application of the foregoing data to the goal-programming model using LINGO (version 4), we get the following optimal solution:

> $TPR = 4070$ (Target = 3000); $RRC = 1053$ (Target = 700); $NDI = 99$ (Target = 75); $Y_{11} = 14$; $Y_{12} = 17$; $Y13 = 14$; $Y_{21} = 16$; $Y_{22} = 17$; $Y_{23} = 7$; $Y_{31} = 18$; $Y_{32} = 14$; $Y_{33} = 14$; $NP_{111} = 2$; $NP_{121} = 1$; $NP_{122} = 7$; $NP_{221} = 3$; $NP_{222} = 6$; $NP_{311} = 2$; $NP_{312} = 6$; $NP_{321} = 9$; $NP_{322} = 3$; $E_{111} = 8$; $E_{112} = 6$; $E_{121} = 9$; $E_{122} = 7$; $E_{131} = 8$; $E_{132} = 6$; $E_{211} = 8$; $E_{212} = 8$; $E_{221} = 8$; $E_{222} = 9$; $E_{231} = 4$; $E_{232} = 3$; $E_{312} = 18$; $E_{321} = 14$; $E_{332} = 1$; $F_{111} = 19$; $F_{112} = 1$; $F_{211} = 15$; $F_{212} = 1$; $F_{311} = 8$; $F_{312} = 3$; $F_{121} = 3$; $F_{122} = 12$; $F_{221} = 2$; $F_{222} = 13$; $F_{321} = 1$; $F_{322} = 13$; $V_1 = 1$; $V_2 = 1$.

It is obvious from the foregoing solution that both production facilities were chosen for network design. Also, 70% of the net demand is satisfied by remanufactured products, and the remaining 30% by newly manufactured products.

## 4.3 Second Model (Linear Integer Programming)

In this model, linear integer programming is used to determine the optimal transportation of products for a generic reverse supply chain involving collection centers, remanufacturing facilities, and demand centers. Section 4.3.1 presents the model formulation, while a numerical example is given in Section 4.3.2.

### 4.3.1 Formulation of the Model

*Minimize*

$$\underbrace{\sum_i \sum_j C_i \cdot T_{ij}}_{\text{Retrieval Costs}} + \underbrace{\sum_i \sum_j TC_{ij} \cdot T_{ij} + \sum_j \sum_k TR_{jk} \cdot N_{jk}}_{\text{Transportation Costs}} + \underbrace{\sum_j \sum_k RC_j \cdot N_{jk}}_{\text{Remanufacturing Costs}}$$

$$\underbrace{+\sum_i \sum_j (C_i / 4) \cdot T_{ij} + \sum_j \sum_k (RC_j / 4) \cdot N_{jk}}_{\text{Inventory Costs}} \tag{4.21}$$

where $C_i$ is the retrieval cost of each product at collection center *i*, $T_{ij}$ is the number of products to be transported from collection center *i* to remanufacturing facility *j*, $TC_{ij}$ is the cost associated with the transportation of one product from collection center *i* to remanufacturing facility *j*, $TR_{jk}$ is the cost associated with the transportation of one product from remanufacturing facility *j* to demand center *k*, $RC_j$ is the remanufacturing cost of each product at remanufacturing facility *j*, and $N_{jk}$ is the number of products to be transported from remanufacturing facility *j* to demand center *k*.
*subject to*
Remanufactured product demand ($D_k$) must be satisfied at each demand center.

$$\sum_j N_{jk} = D_k \tag{4.22}$$

The total number of products remanufactured in a remanufacturing facility cannot exceed the total number of products received by this facility.

$$\sum_i T_{ij} \geq \sum_k N_{jk}; \forall j \tag{4.23}$$

The remanufactured product storage capacity of a remanufacturing facility cannot be exceeded:

$$\sum_k s_1 \cdot N_{jk} \leq SC_{1j} \cdot Y_j; \forall j \tag{4.24}$$

where $s_1$ is the space requirement for one unit of remanufactured product, $SC_{1j}$ is the storage capacity for remanufactured products at remanufacturing facility $j$, and $Y_j$ is the binary variable for the selection of remanufacturing facility $j$.

The used product storage capacity of a collection center cannot be exceeded:

$$\sum_j s_2 \cdot T_{ij} \leq SC_i; \forall i \tag{4.25}$$

where $s_2$ is the space requirement for one unit of used product, and $SC_i$ is the storage capacity of collection center $i$.

The used product storage capacity of a remanufacturing facility cannot be exceeded:

$$\sum_i s_2 \cdot T_{ij} \leq SC_{2j} \cdot Y_j; \forall j \tag{4.26}$$

where $SC_{2j}$ is the storage capacity for used products at remanufacturing facility $j$.

Transported product quantities must be nonnegative numbers:

$$T_{ij} \geq 0; \forall i, j \tag{4.27}$$

$$N_{jk} \geq 0; \forall j, k \tag{4.28}$$

The capacity of a remanufacturing facility for the remanufacture of products cannot be exceeded:

$$\sum_k N_{jk} \leq CP_j; \forall j \tag{4.29}$$

where $CP_j$ is the capacity of remanufacturing facility $j$ for the remanufacture of products.

The total quantity of used products supplied to remanufacturing facilities by a collection center cannot exceed the number of used products received by that collection center:

$$\sum_j T_{ij} \le SP_i ; \forall i \tag{4.30}$$

where $SP_i$ is the supply at collection center $i$.

### 4.3.2 Illustrative Example

Four collection centers, three remanufacturing facilities, and four demand centers are considered in the example (see Figure 4.1). Let the total supply of the used product per period be a Trapezoidal Fuzzy Number (TFN): (500, 550, 650, 700). The defuzzified supply is 600 per period (see Section 2.6, Chapter 2). Assuming equal supply rate at all four collection centers, one

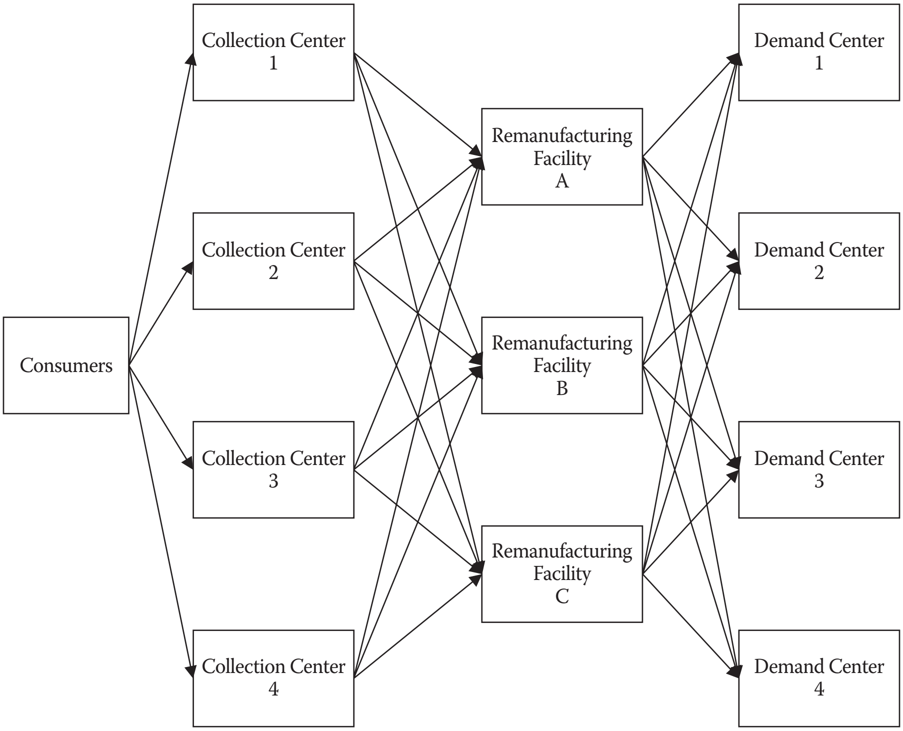

**FIGURE 4.1**
Reverse supply chain.

gets $SP_1 = SP_2 = SP_3 = SP_4 = 150$. The other data used for implementation of the model are as follows:

$C_1 = 22$; $C_2 = 32$; $C_3 = 20$; $C_4 = 40$; $TC_{1A} = 2$; $TC_{2A} = 5$; $TC_{3A} = 3.4$; $TC_{4A} = 5$; $TC_{1B} = 5.3$; $TC_{2B} = 2.4$; $TC_{3B} = 5.5$; $TC_{4B} = 6$; $TC_{1C} = 4.5$; $TC_{2C} = 2.5$; $TC_{3C} = 5$; $TC_{4C} = 6.1$; $TR_{A1} = 3.5$; $TR_{B1} = 2.2$; $TR_{C1} = 4.2$; $TR_{A2} = 4.2$; $TR_{B2} = 3.6$; $TR_{C2} = 2.8$; $TR_{A3} = 2.8$; $TR_{B3} = 3.1$; $TR_{C3} = 3.2$; $TR_{A4} = 2.2$; $TR_{B4} = 3.1$; $TR_{C4} = 4.1$; $RC_A = 5$; $RC_B = 5.3$; $RC_C = 6.6$; $D_1 = 120$; $D_2 = 180$; $D_3 = 125$; $D_4 = 175$; $s_1 = s_2 = 0.6$; $S_{1A} = 600$; $S_{1B} = 600$; $S_{2A} = 600$; $S_{2B} = 600$; $S_{3A} = 600$; $S_{3B} = 600$; $SC_1 = 600$; $SC_2 = 600$; $SC_3 = 600$; $CP_A = 350$; $CP_B = 300$; $CP_C = 320$.

The following optimal solution is obtained by solving the problem with LINGO (Version 9):

$T_{1A} = 150$; that is, 150 products are to be transported from collection center 1 to remanufacturing facility A.

$T_{1B} = 0$, that is, no products are to be transported from collection center 1 to remanufacturing facility B.

$T_{1C} = 0$, that is, no products are to be transported from collection center 1 to remanufacturing facility C.

$T_{2A} = 0$, that is, no products are to be transported from collection center 2 to remanufacturing facility A.

$T_{2B} = 70$, that is, 70 products are to be transported from collection center 2 to remanufacturing facility B.

$T_{2C} = 80$, that is, 80 products are to be transported from collection center 2 to remanufacturing facility C.

$T_{3A} = 150$, that is, 150 products are to be transported from collection center 3 to remanufacturing facility A.

$T_{3B} = 0$, that is, no products are to be transported from collection center 3 to remanufacturing facility B.

$T_{3C} = 0$, that is, no products are to be transported from collection center 3 to remanufacturing facility C.

$N_{A1} = 50$, that is, 50 products are to be transported from remanufacturing facility A to demand center 1.

$N_{A2} = 0$, that is, no products are to be transported from remanufacturing facility A to demand center 2.

$N_{A3} = 125$, that is, 125 products are to be transported from remanufacturing facility A to demand center 3.

$N_{A4} = 175$, that is, 175 products are to be transported from remanufacturing facility A to demand center 4.

$N_{B1} = 70$, that is, 70 products are to be transported from remanufacturing facility B to demand center 1.

$N_{B2} = 0$, that is, no products are to be transported from remanufacturing facility B to demand center 2.

$N_{B3} = 0$, that is, no products are to be transported from remanufacturing facility B to demand center 3.

$N_{B4} = 0$, that is, no products are to be transported from remanufacturing facility B to demand center 4.

$N_{C1} = 0$, that is, no products are to be transported from remanufacturing facility C to demand center 1.

$N_{C2} = 180$, that is, 180 products are to be transported from remanufacturing facility C to demand center 2.

$N_{C3} = 0$, that is, no products are to be transported from remanufacturing facility C to demand center 3.

$N_{C4} = 0$, that is, no products are to be transported from remanufacturing facility C to demand center 4.

## 4.4 Third Model (Linear Physical Programming)

Different components of a generic reverse supply chain (viz., collection centers, remanufacturing facilities, and demand centers) are considered in this model. Optimal transportation quantities for used and remanufactured products are determined using linear physical programming. Modeling details are presented in Section 4.4.1 (using the nomenclature used in Section 4.3). Section 4.4.2 provides a numerical example to illustrate the application of the model.

### 4.4.1 Formulating the Model

#### 4.4.1.1 Class-1S Criteria (Smaller Is Better)

*Total transportation cost per period* ($g_1$) can be presented as follows:

$$g_1 = \sum_i \sum_j TC_{ij} \cdot T_{ij} + \sum_j \sum_k TR_{jk} \cdot N_{jk} \tag{4.31}$$

*Total remanufacturing cost per period* ($g_2$) can be presented as follows:

$$g_2 = \sum_j \sum_k RC_j \cdot N_{jk} \tag{4.32}$$

*Total inventory cost per period* ($g_3$) can be presented as follows:

$$g_3 = \sum_i \sum_j (C_i/4) \cdot T_{ij} + \sum_j \sum_k (RC_j/4) \cdot N_{jk} \tag{4.33}$$

### 4.4.1.2 Class-1H Criteria

*Total retrieval cost per period* ($h_1$) can be presented as follows:

$$h_1 = \sum_i \sum_j C_i \cdot T_{ij} \tag{4.34}$$

### 4.4.1.3 Goal Constraints

$$h_1 \; '' \; MAX\_RET \text{ (The maximum allowed value for retrieval cost)} \tag{4.35}$$

$$g_p - d^+_{pr} \le t^+_{p(r-1)} \tag{4.36}$$

$$g_p \le t^+_{p5} \tag{4.37}$$

$$d^+_{pr} \ge 0 \tag{4.38}$$

### 4.4.1.4 System Constraints

$$\sum_j N_{jk} = D_k \;\; \forall k \text{ (Remanufactured product demand must be satisfied at each demand center)} \tag{4.39}$$

$$\sum_i T_{ij} = SP_i \;\; \forall j \text{ (Each collection center must transport all the used products it received)} \tag{4.40}$$

$$\sum_k N_{jk} = \sum_i T_{ij} \;\; \forall j \text{ (Number of used products must be equal to the number of remanufactured products)} \tag{4.41}$$

$$\sum_i s_2 \cdot T_{ij} \le SC_{2j}; \forall j \text{ (Space occupied by used products is at most the storage capacity of the remanufacturing facility)} \tag{4.42}$$

$$T_{ij} \ge 0; \forall i, j \tag{4.43}$$

$$N_{jk} \ge 0; \forall j, k \tag{4.44}$$

More constraints can be added depending on the desire of the decision maker.

**TABLE 4.1**

Preference Table (in Hundreds)

| Criteria | $t_{p1}{}^{+}$ | $t_{p2}{}^{+}$ | $t_{p3}{}^{+}$ | $t_{p4}{}^{+}$ | $t_{p5}{}^{+}$ |
|---|---|---|---|---|---|
| $g_1$ | 1.5 | 2.5 | 3.5 | 4 | 4.5 |
| $g_2$ | 2 | 3 | 3.5 | 4 | 5 |
| $g_3$ | 1 | 1.75 | 2.25 | 3.25 | 4 |

### 4.4.2 Numerical Example

**TABLE 4.2**

Output of LPP Weight Algorithm

| Criteria | $\Delta\omega_{p2}{}^{+}$ | $\Delta\omega_{p3}{}^{+}$ | $\Delta\omega_{p4}{}^{+}$ | $\Delta\omega_{p5}{}^{+}$ |
|---|---|---|---|---|
| $g_1$ | 0.100000 | 0.120000 | 0.748000 | 1.161600 |
| $g_2$ | 0.100000 | 0.340000 | 0.528000 | 0.096800 |
| $g_3$ | 0.133333 | 0.306667 | 0.044000 | 0.935733 |

In this example, we consider a reverse supply chain similar to the one presented in Figure 4.1. There are three collection centers, two remanufacturing facilities, and three demand centers. The model data is as follows: $C_1 = 0.2$; $C_2 = 0.3$; $C_3 = 0.1$; $TC_{1A} = 0.03$; $TC_{1B} = 0.2$; $TC_{2A} = 0.3$; $TC_{2B} = 2$; $TC_{3A} = 0.2$; $TC_{3B} = 1.5$; $TR_{A1} = 3$; $TR_{A2} = 4$; $TR_{A3} = 0.02$; $TR_{B1} = 3$; $TR_{B2} = 0.2$; $TR_{B3} = 0.1$; $RC_A = 0.3$; $RC_B = 0.1$; $D_1 = 60$; $D_2 = 70$; $D_3 = 85$; $SP_1 = 65$; $SP_2 = 100$; $SP_3 = 50$; $s_1 = s_2 = 0.5$; and $SC_{2A} = SC_{2B} = 450$. Table 4.1 presents the target values for each soft criterion, while the incremental weights obtained by the LPP weight algorithm (Messac et al., 1996) are shown in Table 4.2.

LINGO (version 11) produced the following optimal solution for the model:

$T_{1A} = 0$; $T_{2A} = 100$; $T_{3A} = 45$; $T_{1B} = 65$; $T_{2B} = 0$; $T_{3B} = 5$; $N_{A1} = 60$; $N_{A2} = 0$; $N_{A3} = 85$; $N_{B1} = 0$; $N_{B2} = 70$; and $N_{B3} = 0$.

This solution could be interpreted in a way similar to that in Section 4.3.2.

## 4.5 Other Models

We can classify the reverse and closed-loop supply chain design problems into two main categories: network design and transportation issues.

### 4.5.1 Network Design

There are two commonly studied network design models in the literature, namely, deterministic models and stochastic models. In deterministic models, the uncertainty associated with reverse logistics (RL) and closed-loop networks is not considered, while this uncertainty is integrated into the modeling process in stochastic models (note that here we use the terms "reverse logistics" and "reverse supply chains" interchangeably).

#### 4.5.1.1 Deterministic Models

The majority of the deterministic models focuses only on reverse flows. The most commonly used modeling technique in these models is mixed-integer linear programming (MILP). A two-level location model for recycling sand from construction waste is proposed by Barros et al. (1998). A lower bound is generated using a heuristic procedure based on a linear relaxation strengthened by valid inequalities. The location and size of regional recycling centers for a carpet waste management network are determined by Louwers et al. (1999) using a nonlinear programming model and a linear approximation solution procedure. MILP models for the RL network design for carpet recycling are proposed by Realff et al. (1999) and Realff et al. (2000b). Krikke et al. (1999) solve the RL network design problem of a copier manufacturer by developing an MILP model. The location of remanufacturing/distribution facilities and the optimum quantities of transshipment, production, and stocking for cores and remanufactured products are determined by Jayaraman et al. (1999) employing a binary-mixed integer programming (MIP) model. Fleischmann et al. (2000) investigate several case studies from different industries in order to determine the general characteristics of the product recovery network design problem. Shih (2001) designs an RL system for recycling computers and home appliances by using a mixed-integer programming model. The discrete-time linear analytical model proposed by Hu et al. (2002) solves the network design problem of a multi-time-step, multitype hazardous-waste RL by minimizing the total RL operating costs. Schultmann et al. (2003) design a spent-battery RL network by integrating facility-location planning and flow-sheeting-based process simulation. Jayaraman et al. (2003) develop models and solution procedures for the design of an RL network associated with hazardous products. Determination of the number and location of the collection centers and refurbishing sites and the corresponding flow of hazardous products is the main aim of the study. They were able to solve relatively large problems with up to 40 collection sites and 30 refurbishment sites by using the proposed heuristic concentration procedures combined with heuristic expansion components. However, various important issues including multiple period problems, freight rate discounts, and inventory cost savings resulting from consolidation of returned products are ignored in this study. Wang and Yang (2007) try to improve the heuristics proposed by Jayaraman et al. (2003) by considering the location–allocation problem of recycling e-waste. Exploiting the real-world parameters of Taiwan e-waste recycling industry used by Shih (2001), they develop an MIP model based on the model proposed by Shih. In Amini et al. (2005), an RL network associated with the repair operations of a major international medical diagnostics manufacturer is designed using a binary integer programming. An MIP model for the design of the RL network for a third-party logistics company providing logistics service for the postsale service operations of a manufacturing company is proposed by Du and Evans (2008). They develop a solution methodology by integrating scatter search, the dual simplex method, and the constraint method. Pati et al. (2008) develop a mixed-integer GP formulation in a multiitem, multiechelon, and multifacility decision-making framework to determine the facility location, route, and flow of different varieties of recyclable wastepaper. A multiperiod two-level hierarchical optimization model is proposed by Srivastava (2008a,b) for the RL network design problem. The opening decision for collection centers is determined by the first MILP optimization model based on the minimization of investment (fixed and running costs of facilities and transportation costs). The second MILP optimization model determines the disposition decisions, location, and capacity addition decisions for rework sites at different time periods together with the flows to them from collection centers based on maximization of profit. The location–allocation problem related to the repair facilities of a third-party logistics service provider is solved by Min and Ko (2008) using an MIP model together with a GA. In Lee et al. (2009), the mathematical model associated with an RL network is solved by developing a novel GA. Dehghanian and Mansour (2009) design a product recovery network using a multiobjective GA. Simulated Annealing (SA) is used to solve the MILP model associated with an RL network design problem in Pishvaee et al. (2010a).

The recent trend in the deterministic design of RL networks is the simultaneous consideration of reverse and forward flows. Fleischmann et al. (2001) compare the traditional logistic design with the simultaneous design of forward and reverse network by developing an MILP-based generic Recovery Network Model (RNM). Based on the application of their model to two case studies from the literature, they state that, for many cases, product recovery can be integrated with the existing logistic structure in an efficient way while other cases require the integrated design of reverse and forward logistic networks. Salema et al. (2007) indicate that some important problems of real RL networks (viz., capacity limits on production/storage, multiproduct production, and uncertainty in demand/return flows) were not considered by Fleischmann et al. (2001). In order to fill these gaps, they extend the RNM and develop an MILP formulation for a capacitated multiproduct RL model by considering forward flows. In a follow-up paper, a two-level approach to the same problem is presented by Salema et al. (2005). The location and sorting capabilities of warehouses together with the amount of material to be transported between each pair of sites in a closed loop are determined by Beamon and Fernandes (2004) using a multiperiod MILP model. Sim et al. (2004) integrate Linear Programming (LP) and GAs for the design of a closed-loop supply chain. The linear optimization model proposed by Sheu et al. (2005) considers forward and reverse logistics flows. Zhou et al. (2005) combine Mixed-Integer Nonlinear Programming (MINLP) with a GA in order to solve a distribution problem with forward and reverse flows. Lu and Bostel (2007) solve the location problem of a remanufacturing RL network with forward flows by using a Lagrangian heuristic approach. Ko and Evans (2007) develop a GA-based heuristic procedure to solve the MINLP model associated with the forward/reverse network design problem of a third-party logistics provider. Uster et al. (2007) develop an exact solution for the large-scale MILP model of a closed-loop supply chain network by using Benders decomposition with alternative multiple cuts. Wang et al. (2007) consider product returns while simultaneously determining location and inventory policies in a supply chain by using a bilevel programming-based solution methodology. Lee et al. (2007b) consider the following two objectives while developing a closed-loop supply chain network design model for a third-party logistics provider (3PL): maximization of the returned products shipped from customers back to the collection facilities and minimization of the total costs associated with the forward and reverse logistics operations. First, a compromise solution is developed using fuzzy GP. Then, the problem is solved employing a GA. In Lee et al. (2007a), the MILP model associated with the closed-loop supply chain design of a 3PL is solved by using a GA-based methodology. The location–allocation problem of an end-of-lease computer recovery network is solved by integrating Tabu Search (TS) and network simplex algorithm in Lee and Dong (2008). Demirel and Gökçen (2008) determine the optimal manufacturing, remanufacturing, and transportation quantities together with the optimal locations of disassembly, collection, and distribution facilities by developing an MIP model. A multiechelon closed-loop supply chain involving five retailers, four warehouses, three reprocessing centers, five spare-part markets, three factories, one recycling center, one disposal site, six new module suppliers, and six distribution centers is designed by Mutha and Pokharel (2009) employing a mathematical model. Kannan et al. (2009) integrate GA and particle swarm optimization for the design of a multiechelon closed-loop supply chain in a build-to-order environment. Wang and Hsu (2010) solve the IP model associated with the design of a closed-loop supply chain using a spaning-tree-based GA. The theory of variational inequalities is used in Yang et al. (2009) to formulate and optimize the equilibrium state of a closed-loop supply chain network. Salema et al. (2010) develop a generic model for the simultaneous design and planning of supply chains with reverse flows. They use a graph approach based on the conventional concepts of nodes and arcs. Kannan et al. (2010) develop a GA-based heuristic to solve an MILP model for a closed-loop supply chain network design problem. A memetic-algorithm-based methodology for the integrated design of forward and reverse logistics networks is proposed by Pishvaee et al. (2010b).

In some models, only the issues associated with the collection of used products from consumers are considered. The collection point location problem is formulated as a set covering and MAX-SAT problem in Bautista and Pereira (2006). GAs and GRASP (Greedy Randomized Adaptive Search Procedure) methodologies are employed to solve the set covering and MAX-SAT formulation, respectively. A nonlinear integer program is proposed by Min et al. (2006a) for solving the multi-echelon RL problem involving product returns without considering temporal consolidation issues in a multiple planning horizon. Min et al. (2006b) determine the number and location of initial collection points and centralized return centers by developing a mixed-integer nonlinear model that involves the determination of the exact length of holding time for consolidation at the initial collection points and total RL costs associated with product returns in a multiple planning horizon. They present a GA-based solution methodology. The analytical model proposed by Wojanowski et al. (2007) for the collection facility network design and pricing policy considers the impact of deposit-refund on the sales rate and return rate. Aras and Aksen (2008) analyze the collection center location problem with distance and incentive-dependent returns under a drop-off policy by developing an MINLP. As an extension to this, Aras et al. (2008) consider a pickup policy with capacitated vehicles. In de Figueiredo and Mayerle (2008), minimum-cost recycling collection networks with required throughput are designed by developing an analytical model with the associated algorithmic solution procedure. The uncapacitated facility location model proposed by Cruz-Rivera and Ertel (2009) is used to design a collection network for EOL vehicles in Mexico.

Some researchers present models for the evaluation of collection centers. Bian and Yu (2006) evaluate the alternative RL operation locations for an international electrical manufacturer using AHP. Potential collection center locations are evaluated in Tuzkaya and Gülsün (2008) by integrating ANP and fuzzy logic. Pochampally and Gupta (2008) determine potential facilities from a set of candidate recovery facilities by integrating AHP and fuzzy set theory. The use of AHP and fuzzy AHP for selecting the collection center location in an RL network is investigated by Kannan et al. (2008). The following four phases are used in Pochampally and Gupta (2009) to evaluate the efficiencies of collection and recovery facilities:

1. Criteria for the evaluation of the facilities of interest are identified.
2. Fuzzy ratings of existing facilities are used to construct a neural network that calculates the importance value for each criterion,
3. The overall ratings of the facilities of interest are calculated by employing a fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach.
4. Maximized consensus ratings of the facilities of interest are calculated by using Borda's choice rule.

Another important issue in RL network design is the determination of the appropriate reverse channel structure for the collection of used products. In Savaskan et al. (2004), reverse channel structure selection problem for a single manufacturer single retailer case is investigated. As an extension to this, Savaskan and Van Wassenhove (2006) consider two retailers in a competitive retailing environment. The impact of centralized and decentralized channel structures in the optimal order quantity of a retailer from a manufacturer making new products, and orders remanufactured products from a remanufacturer, is analyzed by Bhattacharya et al. (2006). Centralized as well as remanufacturer- and collector-driven decentralized channels are analyzed by Karakayali et al. (2007). Decentralized assignment of recycling tasks to the companies of a recycling network is achieved by the negotiation-based coordination mechanism developed by Walther et al. (2008). A comparison of centralized and decentralized decision making in an RL system is presented by Hong et al. (2008). In a centralized model, the decisions for the entire system are given by a decision maker, while there are several independent entities individually operated by self-interested parties in the decentralized model. Lee et al. (2011) determine a profitable apportionment of effort between the manufacturer and retailer for different product recovery processes by considering a decentralized RL system with retailer collection. El Korchi and Millet (2011) develop a detailed practical framework for designing the reverse logistics channel (RLC). In this framework, first, the current RLC structure is evaluated by comparing the current structure with the alternatives. Then, the potential generic RLC structure is selected from among the 18 generic structures by applying the following criteria: feasibility assessment, economic assessment, environmental assessment, and social assessment.

#### *4.5.1.2 Stochastic Models*

There is a high level of uncertainty associated with the quality and quantity of returns. Stochastic network design models consider this uncertainty explicitly in the model-building process. One of the commonly used techniques to deal with the uncertainty in RL network design is robust optimization. The robust MILP model proposed by Realff et al. (2000a, 2004) search for solutions close to the mathematically optimal solutions for a set of alternative scenarios identified by a decision maker. Another robust MILP model is developed by Hong et al. (2006) based on the maximization of the system net profit for specified deterministic parameter values in each scenario. A robust solution for all of the scenarios is determined by employing a min–max robust optimization methodology.

Stochastic programming has also been used in stochastic modeling of the RL network design problem. The sand recycling case study given in Barros et al. (1998) is solved by Listes and Dekker (2005) using a stochastic-programming-based approach. A generic stochastic model for closed-loop supply chains is developed by Listes (2007). In Lee et al. (2007c), a product recovery network design problem is solved by employing a stochastic-programming-based approach. The randomness associated with recovery, processing, and demand volumes is considered in the stochastic programming model developed by Chouinard et al. (2008). A sample average approximation-based heuristic is used to solve the problem. Lee and Dong (2009) integrate sample average approximation and SA to solve a stochastic programming model associated with the location and allocation decisions of an RL network under uncertainty.

Lieckens and Vandaele (2007) employ a GA-based technique, Differential Evolution, to solve the MINLP model integrating a conventional RL MILP model with a queuing model to deal with the dynamic and stochastic aspects of RL networks.

Fuzzy programming is used by Qin and Ji (2010) to deal with the uncertainty associated with the design of RL networks. Fuzzy simulation and GAs are integrated for the design of an RL network. Pishvaee and Torabi (2010) develop a fuzzy solution approach by combining a number of efficient solution approaches for the design of a closed-loop supply chain network.

#### *4.5.1.3 Simultaneous Consideration of Network and Product Design Issues*

Product design issues are explicitly considered in some of the reverse or closed-loop supply chain network design models. The decisions on both the design structure of a product, that is, modularity, reparability, and recyclability, and the design structure of the logistic network can be assisted by the MILP model developed by Krikke et al. (2003). Krikke et al. (2004) analyze the role of product modularity on closed-loop supply chain design. The impact of product modularity on RL strategy is investigated by Fernandez and Kekale (2005).

### 4.5.2 Transportation Issues

Different versions of the Vehicle Routing Problem (VRP) have been used by researchers in order to determine the vehicle routes in RL networks. In some VRP models, only return flows are considered. Heuristic methods are provided by Mourao and Almeida (2000) and Mourao and Amado (2005) for the solution of the mixed capacitated arc routing problem of a refuse collection network. VRP is used by Blanc et al. (2004) to obtain reliable estimates of transportation costs in a recycling network redesign problem. A multidepot pickup and delivery model with capacitated vehicles and alternative delivery locations is proposed by Blanc et al. (2006) for the collection of containers from EOL vehicle dismantlers in the Netherlands. Route generation and set partitioning are integrated to solve the model. In Schultmann et al. (2006), TS is used to solve the symmetric capacitated VRP to generate a tour schedule with minimal cost for an EOL auto RL network. Krikke et al. (2008) solve the VRP associated with the low-frequency collection of materials disassembled from EOL vehicles by integrating route generation and set partitioning. Kim et al. (2009) employ TS to solve a VRP for an RL network in South Korea.

In some VRP models, both return and delivery flows are considered. In the RL system considered by Dethloff (2001), customers have both pickup and delivery demands. After modeling this system as a Vehicle Routing Problem with Simultaneous Delivery and Pick-up (VRPSDP), he develops a heuristic construction procedure to solve the problem. The VRP with backhauls is solved by Dethloff (2002) by using the heuristic procedure proposed in Dethloff (2001). After modeling VRPSDP as an MILP model, Gribkovskaia et al. (2007) develop general solutions using conventional construction and improvement heuristics and TS. Alshamrani et al. (2007) develop a heuristic procedure to develop route design and pickup strategies simultaneously for the blood distribution network of the American Red Cross in which products are delivered from a central processing point to customers (stops) in one period are available for return to the central point in the following period.

## 4.6 Conclusions

In this chapter, three models were presented to illustrate the various issues associated with the design of reverse and closed-loop supply chains. The first model determined the number of units of used product of each type to be picked for remanufacturing; identified the efficient production facilities, and achieved the optimal transfer of goods across a closed-loop supply chain in one unified solution. In the second model, linear integer programming was used to determine the optimal transportation of products for a generic reverse supply chain involving collection centers, remanufacturing facilities, and demand centers. Optimal transportation quantities for used and remanufactured products were determined using linear physical programming in the third model. A review of recent literature on the design of reverse and closed-loop supply chains was provided in the previous section.

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# 5

# *Selection of Used Products*

## 5.1 The Issue

Companies produce different types of products. The number and type of components, connection types, and materials differ among these product types. These characteristics greatly determine the cost of end-of-life processing operations when the products reach their end of life. A company will select only those products for which the costs associated with collection and reprocessing are less than the revenues from recycle or resale of the products' components.

In this chapter we consider the used product selection issue in remanufacturing by considering two scenarios. In the first scenario, classical numerical constraints are used to present evaluation criteria, while ranges of different degrees of desirability are employed in the second scenario. The first model presented in the chapter illustrates the first scenario by using linear integer programming. The second model considers scenario 2 and uses linear physical programming.

## 5.2 First Model (Linear Integer Programming)

### 5.2.1 Modeling Process

The cost–benefit function was first used by Veerakamolmal and Gupta (1999) for the selection of the best used product from a set of candidate used products. There are four terms in this function, namely, recycling revenue, resale revenue, disposal cost, and reprocessing cost. The value of the function is calculated by taking the difference between the sum of the revenue terms and the sum of the cost terms. The used product having the maximum cost–benefit function value is selected for reprocessing. However, this method has two implicit assumptions that damage its applicability in a realistic remanufacturing system: (1) There is no failed or missing component in a used product. (2) There is no change in the original multiplicities of a component in a used product during product usage.

In order to relax these assumptions, Pochampally et al. (2009a) proposed a modified cost–benefit function. In this approach, the probability of failed and missing components in a used product of interest is incorporated into the cost–benefit function. Then, the most economical used product is determined by formulating and implementing a linear integer programming model for each candidate used product.

### *5.2.1.1 Modified Cost–Benefit Function*

Total resale revenue ($SR_x$), total recycling revenue ($RR_x$), total reprocessing cost ($RPC_x$), total disposal cost ($DC_x$), and collection cost ($CC_x$) are the terms considered in the modified cost–benefit function, which can be written as follows:

$$Z = RR_x + SR_x - CC_x - DC_x - RPC_x \tag{5.1}$$

where $Z$ is the overall profit. We can explain the terms of $Z$ as follows:

*Total recycling revenue:* The following factors affect this term—percentage of recyclable contents in each component ($PRC_{xj}$); the weight of the components ($W_{xj}$); the recycling revenue index ($RI_{xj}$) (0 = lowest, 10 = highest); the number of components ($M_{xj}$); the probability of breakage ($pb_{xj}$); the probability of missing components ($pm_{xj}$); and recycling revenue factor ($F_{rr}$). The following equation presents the recycling revenue equation:

$$RR_x = \sum_{j\ C_{xj}\varepsilon(Root_x)} \{PRC_{xj}\cdot W_{xj}\cdot RI_{xj}\cdot(M_{xj}\cdot(1-pm_{xj}) - M_{xj}(1-pb_{xj}-pm_{xj})\cdot X_{xj})\}\cdot F_{rr} \tag{5.2}$$

where $X_{xj}$ is the decision variable signifying the selection of component $j$ to be retrieved from used product $x$ for reuse ($X_{xj}$ = 1 for reuse, 0 for recycle).

*Total resale revenue:* The following factors affect this term—resale value of individual components of the used product ($RV_{xj}$); the number of components ($M_{xj}$); the probability of breakage ($pb_{xj}$); and the probability of missing components ($pm_{xj}$). The revenue equation can be given as follows:

$$SR_x = \sum_{j\ C_{xj}\varepsilon(Root_x)} \{RV_{xj}\cdot M_{xj}\cdot(1-pb_{xj}-pm_{xj})\cdot X_{xj}\} \tag{5.3}$$

*Collection cost:* $CC_{xj}$ is the average cost associated with the collection of used product $x$ from the consumers.

*Total disposal cost:* The following factors affect this term—disposal cost index ($DCI_{xj}$) (0 = lowest, 10 = highest); the percentage of recyclable contents in each component ($PRC_{xj}$); the weight of the components ($W_{xj}$); the number of components ($M_{xj}$); the probability of breakage ($pb_{xj}$); the probability of missing components ($pm_{xj}$), and the disposal cost factor ($F_{dc}$). The following equation presents the disposal cost expression:

$$DC_x = \sum_{j \; C_{xj} \varepsilon (Root_x)} \{DCI_{xj} \cdot W_{xj} \cdot (1 - PRC_{xj}) \cdot (M_{xj} \cdot (1 - pm_{xj}) - M_{xj} \cdot (1 - pb_{xj} - pm_{xj}) \cdot X_{xj})\} \cdot F_{dc} \tag{5.4}$$

*Total reprocessing cost:* Disassembly time of the root node of the used product ($T(Root_x)$), the disassembly time of each subassembly in the used product ($T(S_{xk})$), and the reprocessing cost per unit time ($RC$) are the factors used in the calculation of total reprocessing cost. The following equation presents the reprocessing cost expression:

$$RPC_x = \quad T(Root_x) + \sum_{k=1}^{L_x} T(S_{xk}) \quad \cdot RC \tag{5.5}$$

where $L_x$ is the number of subassemblies in used product $x$.

#### 5.2.1.2 Linear Integer Programming Model

In order to maximize the cost–benefit associated with the reprocessing of used product $x$, a linear integer programming model can be developed as follows:

$$\text{Maximize } Z_x = RR_x + SR_x - CC_x - DC_x - RPC_x \tag{5.6}$$

subject to $X_{xj} = 0$ or 1 for all $x$ and $j$.

This model allows us to evaluate the feasible combinations of components to be retrieved from a used product. It also compares the combination with the highest cost–benefit from one product against others.

### 5.2.2 Example

We illustrate this method by presenting an example. In this example, two products are considered (see Figure 5.1 and Figure 5.2). Component characteristics for used product 1 and used product 2 are presented in

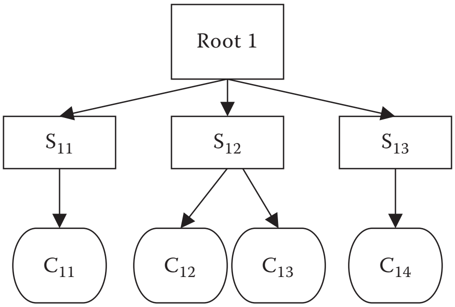

**FIGURE 5.1**
Subassemblies and components of product 1.

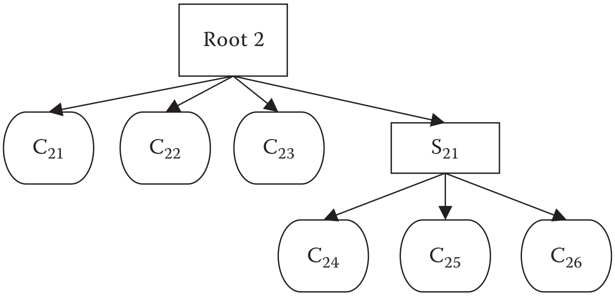

**FIGURE 5.2**
Subassemblies and components of product 2.

Tables 5.1 and 5.2, respectively. In addition, $CC_1$ =15 \$/product; $CC_2$ =25 \$/product; $CF$ = 0.30 \$/lb; $CD$ = 0.60 \$/min.; $DF$ = 0.2 \$/lb; $T(Root\ 1)$ = 2 min.; $T(Root\ 2)$ = 3 min.; $T(S_{11})$ = 4 min.; $T(S_{12})$ = 6 min., $T(S_{13})$ = 3 min.; $T(S_{21})$ = 7 min.

LINGO was used to solve the model with the foregoing data. The total profit for used product 1 is \$46.16, whereas the total profit for used product 2 is \$68.50. Based on these profit values, used product 2 must be selected for EOL processing.

**TABLE 5.1**
Component Characteristics for Used Product 1

| Component | $RV_{1j}$ | $N_{1j}$ | $W_{1j}$ | $RI_{1j}$ | $RCP_{1j}$ | $DI_{1j}$ | $pb_{1j}$ | $pm_{1j}$ |
|---|---|---|---|---|---|---|---|---|
| $C_{11}$ | 7.5 | 1 | 5 | 8 | 70% | 4 | 0.2 | 0.3 |
| $C_{12}$ | 5 | 5 | 2.5 | 7.5 | 50% | 8 | 0.1 | 0 |
| $C_{13}$ | 2.5 | 4 | 0.8 | 9 | 35% | 3 | 0 | 0.5 |
| $C_{14}$ | 1.2 | 2 | 1 | 3 | 65% | 2 | 0 | 0.1 |

**TABLE 5.2**

Component Characteristics for Used Product 2

| Component | $RV_{2j}$ | $N_{2j}$ | $W_{2j}$ | $RI_{2j}$ | $RCP_{2j}$ | $DI_{2j}$ | $pb_{2j}$ | $pm_{2j}$ |
|---|---|---|---|---|---|---|---|---|
| $C_{21}$ | 3.5 | 4 | 6 | 2 | 90% | 1 | 0.3 | 0 |
| $C_{22}$ | 2.8 | 3 | 0.8 | 8.5 | 30% | 3 | 0.2 | 0.5 |
| $C_{23}$ | 5 | 6 | 4 | 9 | 55% | 2 | 0 | 0.5 |
| $C_{24}$ | 1.5 | 2 | 3 | 6 | 80% | 5 | 0 | 0.2 |
| $C_{25}$ | 2.1 | 1 | 1 | 3 | 35% | 9 | 0.1 | 0.1 |
| $C_{26}$ | 4 | 2 | 1.5 | 5 | 45% | 6 | 0.1 | 0 |

## 5.3 Second Model (Linear Physical Programming—LPP)

In this section, we present the formulation for the linear physical programming model. Then, a numerical example is presented to illustrate the application of the model.

### 5.3.1 Modeling Details

Class 1S and Class 2S criteria are used in the modeling of the used product selection problem. The explanation of the criteria for each class is presented in the following two sections.

#### *5.3.1.1 Class 1S Criteria (Smaller Is Better)*

*Total collection cost per period ($g_1$)*: The supply of product $x$ per period ($SUP_x$) is multiplied by the cost of collecting one product from consumers ($CC_x$) to calculate $g_1$:

$$SUP_x \times CC_x \tag{5.7}$$

*Total reprocessing cost per period ($g_2$):* Disassembly time of the root node ($T(Rootx)$), disassembly time of each subassembly ($T(S_{xk})$), supply of product $x$ per period ($SUP_x$), and the remanufacturing cost per unit time ($RC$) are used to calculate $g_2$:

$$SUP_x \cdot \quad T(Root_x) + \sum_{k=1}^{L_x} T(S_{xk}) \quad \cdot RC \tag{5.8}$$

*Total disposal cost per period ($g_3$)*: The component disposal cost is multiplied by the number of units of components disposed to calculate $g_3$:

$$\sum_{y} [SUP_x \cdot DCI_{xj} \cdot W_{xj} \cdot (1 - PRC_{xj}) \cdot \{M_{xj} \cdot (1 - pm_{xj}) - M_{xj} \cdot (1 - pb_{xj} - pm_{xj})\}] \cdot F_{dc} \tag{5.9}$$

### *5.3.1.2 Class 2S Criteria (Larger Is Better)*

*Total reuse revenue per period* ($g_4$): The supply of product $x$ per period ($SUP_x$), the resale value of component $j$ ($RV_{xj}$), the multiplicity of component $j$ ($M_{xj}$), and the breakage and missing probabilities of component $j$ ($pb_{xj}$, $pm_{xj}$) are the factors affecting this criterion. The equation for reuse revenue can be presented as follows:

$$\sum_j [SUP_x \cdot RV_{xj} \cdot M_{xj} \cdot (1 - pb_{xj} - pm_{xj})] \tag{5.10}$$

*Total recycling revenue per period* ($g_5$): The supply of product $x$ per period ($SUP_x$), the recycling revenue index of component $j$ ($RI_{xj}$), the percentage of recyclable content in component $j$ ($PRC_{xj}$), the multiplicity of component $j$ ($M_{xj}$), the weight of component $j$ ($W_{xj}$), the recycling revenue factor ($F_{rr}$), and the breakage and missing probabilities of component $j$ ($pb^{xj}$, $pm_{xj}$) are the factors affecting this criterion. The recycling revenue equation can be written as

$$\sum_y [SUP_x \cdot RI_{xj} \cdot W_{xj} \cdot PRC_{xj} \cdot \{M_{xj} \cdot (1 - pm_{xj}) - M_{xj}(1 - pm_{xj} - pb_{xj})\} \cdot F_{rr}] \tag{5.11}$$

### 5.3.2 Example

The three product structures considered in this example can be seen in Figures 5.3 through 5.5, respectively, and Tables 5.3 through 5.5 show the component characteristics for used product 3, 4, and 5, respectively. Table 5.6 presents the target values for the criteria. Criteria values for each product are provided in Table 5.7. Incremental weights obtained using the LPP weight algorithm are given in Table 5.8. Tables 5.9, 5.10, and 5.11 show the deviations of criteria values from the target values for the three products, respectively.

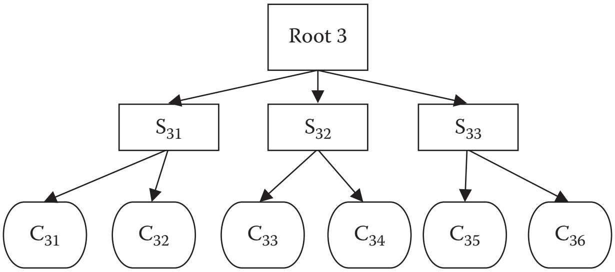

**FIGURE 5.3**
Subassemblies and components of product 3.

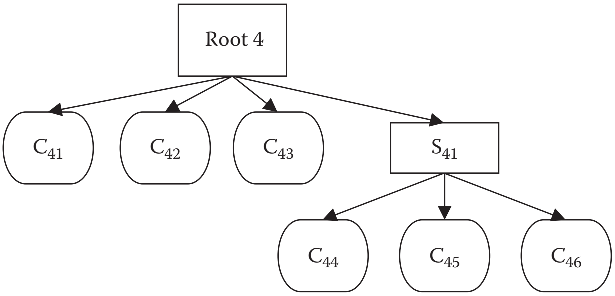

**FIGURE 5.4**
Subassemblies and components of product 4.

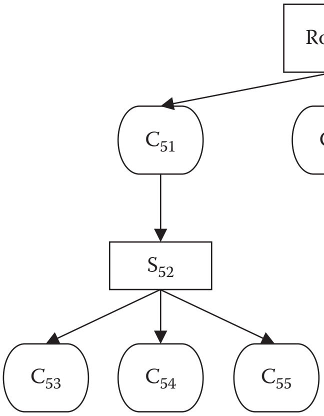

**FIGURE 5.5**
Subassemblies and components of product 5.

**TABLE 5.3**

Component Characteristics for Used Product 3

| Component | $RV_{3j}$ | $N_{3j}$ | $W_{3j}$ | $RI_{3j}$ | $RCP_{3j}$ | $DI_{3j}$ | $pb_{3j}$ | $pm_{3j}$ |
|---|---|---|---|---|---|---|---|---|
| $C_{31}$ | 4 | 2 | 4.5 | 6 | 30% | 3 | 0.1 | 0.2 |
| $C_{32}$ | 4 | 3 | 4 | 7 | 40% | 5 | 0.3 | 0.5 |
| $C_{33}$ | 2 | 5 | 1 | 3 | 70% | 8 | 0.5 | 0.0 |
| $C_{34}$ | 3 | 1 | 2 | 5 | 90% | 1 | 0.1 | 0.2 |
| $C_{35}$ | 2 | 1 | 3 | 4 | 60% | 4 | 0.2 | 0.3 |
| $C_{36}$ | 4 | 2 | 4 | 6 | 70% | 2 | 0.1 | 0.3 |

**TABLE 5.4**

Component Caracteristics for Used Product 4

| Component | $RV_{4j}$ | $N_{4j}$ | $W_{4j}$ | $RI_{4j}$ | $RCP_{4j}$ | $DI_{4j}$ | $pb_{4j}$ | $pm_{4j}$ |
|---|---|---|---|---|---|---|---|---|
| $C_{41}$ | 2 | 2 | 4 | 1 | 80% | 2 | 0.1 | 0.3 |
| $C_{42}$ | 2 | 2 | 1.8 | 7.5 | 40% | 5 | 0.3 | 0 |
| $C_{43}$ | 3 | 4 | 2.5 | 7 | 65% | 4 | 0.2 | 0.4 |
| $C_{44}$ | 2 | 5 | 4.5 | 5 | 60% | 7 | 0.1 | 0.3 |
| $C_{45}$ | 4 | 1 | 1.2 | 4 | 55% | 7 | 0 | 0.1 |
| $C_{46}$ | 3 | 1 | 2.5 | 8 | 25% | 4 | 0.3 | 0.5 |

**TABLE 5.5**

Component Characteristics for Used Product 5

| Component | $RV_{5j}$ | $N_{5j}$ | $W_{5j}$ | $RI_{5j}$ | $RCP_{5j}$ | $DI_{5j}$ | $pb_{5j}$ | $pm_{5j}$ |
|---|---|---|---|---|---|---|---|---|
| $C_{51}$ | 2 | 3 | 5 | 5 | 60% | 2 | 0.1 | 0.2 |
| $C_{52}$ | 3 | 2 | 3.8 | 6.5 | 25% | 5 | 0.1 | 0.1 |
| $C_{53}$ | 3 | 4 | 4.5 | 8.5 | 70% | 4 | 0.1 | 0.2 |
| $C_{54}$ | 2 | 4 | 1.3 | 4 | 75% | 9 | 0.2 | 0 |
| $C_{55}$ | 4 | 2 | 0.7 | 3 | 75% | 2 | 0 | 0.3 |
| $C_{56}$ | 3 | 2 | 3.5 | 5 | 35% | 4 | 0.1 | 0.3 |

**TABLE 5.6**

Target Values for the LPP Model

| Criteria | $t_{p1}+$ | $t_{p2}+$ | $t_{p3}+$ | $t_{p4}+$ | $t_{p5}+$ |
|---|---|---|---|---|---|
| $g_1$ | 7000 | 11000 | 13000 | 15000 | 18000 |
| $g_2$ | 3000 | 5000 | 8000 | 11000 | 13000 |
| $g_3$ | 4000 | 5000 | 7000 | 9000 | 11000 |
| **Criteria** | $t_{p1}-$ | $t_{p2}-$ | $t_{p3}-$ | $t_{p4}-$ | $t_{p5}-$ |
| $g_4$ | 9000 | 11000 | 13000 | 17000 | 20000 |
| $g_5$ | 2000 | 4000 | 7000 | 9000 | 13000 |

**TABLE 5.7**

Criteria Values for the LPP Model

| Criteria | Used Product 3 | Used Product 4 | Used Product 5 |
|---|---|---|---|
| $g_1$ | 10000 | 8000 | 15000 |
| $g_2$ | 7000 | 6000 | 9000 |
| $g_3$ | 4030 | 2982 | 1003 |
| $g_4$ | 20900 | 20200 | 24100 |
| $g_5$ | 14722.5 | 13799.5 | 13513.5 |

**TABLE 5.8**

Weights for LPP

| Criteria | $\Delta w_{p2}+$ | $\Delta w_{p3}+$ | $\Delta w_{p4}+$ | $\Delta w_{p5}+$ | $\Delta w_{p2}-$ | $\Delta w_{p3}-$ | $\Delta w_{p4}-$ | $\Delta w_{p5}-$ |
|---|---|---|---|---|---|---|---|---|
| $g_1$ | 0.025000 | 0.085000 | 0.132000 | 0.112933 | — | — | — | — |
| $g_2$ | 0.050000 | 0.023333 | 0.088000 | 0.371067 | — | — | — | — |
| $g_3$ | 0.100000 | 0.010000 | 0.132000 | 0.290400 | — | — | — | — |
| $g_4$ | — | — | — | — | 0.050000 | 0.059500 | 0.010402 | 0.230213 |
| $g_5$ | — | — | — | — | 0.050000 | 0.023000 | 0.166805 | 0.022781 |

**TABLE 5.9**

Deviations from Target Values for Used Product 3

| Criteria | $s = 2$ | $s = 3$ | $s = 4$ | $s = 5$ |
|---|---|---|---|---|
| $g_1$ | 3000 | 1000 | 3000 | 5000 |
| $g_2$ | 4000 | 2000 | 1000 | 4000 |
| $g_3$ | 30 | 970 | 2970 | 4970 |
| $g_4$ | 900 | 3900 | 7900 | 9900 |
| $g_5$ | 1722.5 | 7722.5 | 10722.5 | 12722.5 |

**TABLE 5.10**

Deviations from Target Values for Used Product 4

| Criteria | $s = 2$ | $s = 3$ | $s = 4$ | $s = 5$ |
|---|---|---|---|---|
| $g_1$ | 1000 | 3000 | 5000 | 7000 |
| $g_2$ | 3000 | 1000 | 2000 | 5000 |
| $g_3$ | 1018 | 2018 | 4018 | 6018 |
| $g_4$ | 200 | 3200 | 7200 | 9200 |
| $g_5$ | 799.5 | 4799.5 | 6799.5 | 9799.5 |

**TABLE 5.11**

Deviations from Target Values for Used Product 5

| Criteria | $s = 2$ | $s = 3$ | $s = 4$ | $s = 5$ |
|---|---|---|---|---|
| $g_1$ | 8000 | 4000 | 2000 | 0 |
| $g_2$ | 6000 | 4000 | 1000 | 2000 |
| $g_3$ | 2997 | 3997 | 5997 | 7997 |
| $g_4$ | 4100 | 7100 | 11100 | 13100 |
| $g_5$ | 513.5 | 4513.5 | 6513.5 | 9513.5 |

**TABLE 5.12**

Ranking of Used Products

| Used Product | Score | Rank |
|---|---|---|
| 1 | 9768.102 | 1 |
| 2 | 10236.233 | 2 |
| 3 | 10672.468 | 3 |

We employ Equation 2.23 in order to calculate the total score for each product (see Table 5.12). Used product 1 is the best choice since the alternatives with lower scores are more desirable.

## 5.4 Other Models

There are mainly two techniques of used product selection: cost–benefit function and linear physical programming. The cost–benefit function technique is preferred if the evaluation criteria are given in terms of classical numerical constraints. A cost–benefit function for the selection of the best product for reprocessing from a set of candidate used products is presented by Veerakamolmal and Gupta (1999). They calculate the value of the cost–benefit function by subtracting the sum of revenue terms from the sum of cost terms. Pochampally and Gupta (2005) and Pochampally et al. (2009b) present a modified version of this cost–benefit function by considering the probability of breakage and the probability of missing components in the used product of interest. They also develop an integer linear programming model for the maximization of the modified cost–benefit function. A fuzzy cost–benefit function involving the uncertainty associated with revenues and costs is proposed by Pochampally and Gupta (2008).

Linear physical programming is the most appropriate solution methodology if the evaluation criteria are presented in terms of a range of different degrees of desirability. For this case, Pochampally et al. (2009a) present an LPP formulation.

## 5.5 Conclusions

In this chapter we presented two models for used product selection in remanufacturing. Linear integer programming was used in the first model, while linear physical programming was employed in the second model. A review of recent literature on used product selection was provided in the previous section.

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# 6

# *Evaluation of Remanufacturing Facilities*

## 6.1 The Issue

Researchers developed many quantitative models for the design of reverse supply chains. In the majority of these models, it is assumed that all the remanufacturing facilities that are engaged in a supply chain have enough potential to efficiently reprocess the incoming used products. However, there are usually differences among recovery facilities in terms of quality, cost, throughput, and customer service. Hence, there is a need for the evaluation of remanufacturing facilities prior to the network design of a reverse supply chain.

In this chapter we present two methodologies for the comparison of remanufacturing facilities. The first methodology uses TOPSIS (technique for order preference by similarity to ideal solution) to evaluate potential remanufacturing facilities. The second one estimates the total cost associated with a remanufacturing facility.

## 6.2 First Model (TOPSIS)

We use TOPSIS (see Section 2.4, Chapter 2) in this section to evaluate candidate remanufacturing facilities (Pochampally and Gupta, 2004). In the TOPSIS hierarchy presented in Figure 6.1, the objective is placed at the first level. The last level contains candidate recovery facilities. The level in the middle contains criteria used to compare candidate recovery facilities. One of the criteria, the fixed cost of the facility (FCF), is also used in forward supply chain facility selection problems. However, the following four criteria must be explained in detail since they are peculiar to remanufacturing systems.

- *Difference between the average quality of remanufactured products (QRG) and the average quality of incoming used products (QIP)*: QRG cannot be used as an independent criterion since it depends on QIP. That is why the difference between QRG and QIP is used as a criterion.

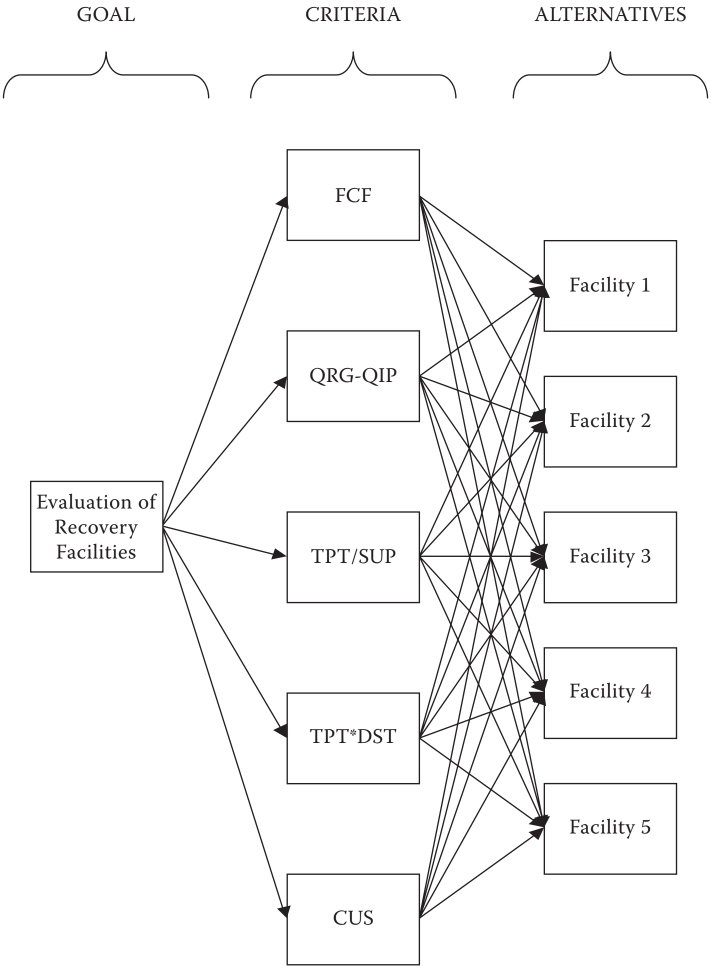

**FIGURE 6.1**
Hierarchical structure for TOPSIS.

- *Ratio of throughput (TPT) to supply of used products (SUP)*: The TPT of a remanufacturing facility depends on the SUP. In other words, a low SUP may lead to a low TPT, whereas a high SUP may result in a high TPT. In order to compensate for the high or low SUP, we used the ratio of TPT to SUP as a criterion.
- *Multiplication of average disassembly time (DST) by throughput (TPT)*: Another factor affecting TPT is DST. A low TPT may be experienced for a high DST, while a low DST may lead to a high TPT. The effect of DST can be compensated for by considering the multiplication of DST by TPT as a criterion.

- *Customer service (CUS)*: The following factors should be considered while analyzing CUS associated with a remanufacturing facility:
    - Compliance with environmental regulations
    - Utilization of the incentives provided by the government
    - Type of incentives given to the collection centers supplying the used products
    - Type of incentives given to the customers buying the reprocessed goods

The seven stages of TOPSIS (see Section 2.4, Chapter 2) can be applied to the problem as follows:

### STAGE 1:

Pairwise comparison matrix for the criteria is given in Table 6.1. Application of the eigenvalue method to this table results in the criteria impacts presented in Table 6.2. Table 6.3 depicts the decision matrix.

### STAGE 2:

Equation (2.5) is applied to each element of Table 6.3 in order to create the normalized decision formula given in Table 6.4.

### STAGE 3:

Criteria impacts presented in Table 6.2 and the normalized decision matrix given in Table 6.4 are employed to form the weighted normalized decision matrix given in Table 6.5.

**TABLE 6.1**

Pairwise Comparison Matrix for Criteria

| Criteria | FCF | QRG–QIP | TPT/SUP | TPT*DST | CUS |
|---|---|---|---|---|---|
| FCF | 1 | 1/3 | 4 | 1 | 1/2 |
| QRG–QIP | 3 | 1 | 6 | 5 | 2 |
| TPT/SUP | 1/4 | 1/6 | 1 | 1/5 | 1/5 |
| TPT*DST | 1 | 1/5 | 5 | 1 | 1/5 |
| CUS | 2 | 1/2 | 5 | 5 | 1 |

**TABLE 6.2**

Impact of Each Criterion

| Criteria | Impacts |
|---|---|
| FCF | 0.2918 |
| QRG–QIP | 0.1325 |
| TPT/SUP | 0.4194 |
| TPT*DST | 0.1135 |
| CUS | 0.0428 |

**TABLE 6.3**

Decision Matrix

| Criteria | FCF | QRG–QIP | TPT/SUP | TPT*DST | CUS |
|---|---|---|---|---|---|
| Facility 1 | 1 | 4 | 3 | 2 | 1 |
| Facility 2 | 5 | 6 | 1 | 1 | 2 |
| Facility 3 | 4 | 5 | 2 | 2 | 2 |
| Facility 4 | 4 | 2 | 3 | 1 | 3 |
| Facility 5 | 6 | 7 | 3 | 2 | 1 |

**TABLE 6.4**

Normalized Decision Matrix

| Criteria | FCF | QRG–QIP | TPT/SUP | TPT*DST | CUS |
|---|---|---|---|---|---|
| Facility 1 | 0.1031 | 0.3508 | 0.5303 | 0.5345 | 0.2294 |
| Facility 2 | 0.5157 | 0.5262 | 0.1768 | 0.2673 | 0.4588 |
| Facility 3 | 0.4126 | 0.4385 | 0.3536 | 0.5345 | 0.4588 |
| Facility 4 | 0.4126 | 0.1754 | 0.5303 | 0.2673 | 0.6883 |
| Facility 5 | 0.6189 | 0.6139 | 0.5303 | 0.5345 | 0.2294 |

**TABLE 6.5**

Weighted Normalized Decision Matrix

| Criteria | FCF | QRG–QIP | TPT/SUP | TPT*DST | CUS |
|---|---|---|---|---|---|
| Facility 1 | 0.0301 | 0.0465 | 0.2224 | 0.0607 | 0.0098 |
| Facility 2 | 0.1505 | 0.0697 | 0.0742 | 0.0303 | 0.0196 |
| Facility 3 | 0.1204 | 0.0581 | 0.1483 | 0.0607 | 0.0196 |
| Facility 4 | 0.1204 | 0.0232 | 0.2224 | 0.0303 | 0.0295 |
| Facility 5 | 0.1806 | 0.0813 | 0.2224 | 0.0607 | 0.0098 |

### STAGE 4:

The ideal and the negative ideal solutions are determined next. In the weighted normalized decision matrix, the maximum rank in a column is the ideal solution, and the minimum rank is the negative ideal solution for the criteria associated with this column.

### STAGE 5:

Equations (2.9) and (2.10) are used to calculate the separation distances presented in Table 6.6 for each remanufacturing facility.

### STAGE 6:

The relative closeness coefficients (see Table 6.7) are calculated for remanufacturing facilities using Equation (2.11).

**TABLE 6.6**

Separation Distances

| Remanufacturing Facility | $S^*$ | $S^-$ |
|---|---|---|
| Facility 1 | 0.1531 | 0.1557 |
| Facility 2 | 0.1294 | 0.1559 |
| Facility 3 | 0.1260 | 0.0988 |
| Facility 4 | 0.1747 | 0.0890 |
| Facility 5 | 0.2212 | 0.0197 |

**TABLE 6.7**

Relative Closeness Coefficients

| Remanufacturing Facility | $C^*$ |
|---|---|
| Facility 1 | 0.5042 |
| Facility 2 | 0.5464 |
| Facility 3 | 0.4395 |
| Facility 4 | 0.3375 |
| Facility 5 | 0.0818 |

### STAGE 7:

The preference order of remanufacturing facilities is created as Facility 2, Facility 1, Facility 3, Facility 4, and Facility 5 since the alternative with the highest relative closeness coefficient is considered to be the best alternative.

## 6.3 Second Model (Cost Model)

In this section we present a remanufacturing facility cost model that includes product, operation, inventory, and transportation-related costs (Sutherland et al., 2010). The effects of product yield, remanufacturing efficiency, transportation cost rate, and product mass on remanufactured product unit cost and remanufacturing facility size are also considered. The total annual cost ($TC$) is given by the following equation:

$$TC = MC + RC + CC + OC + DC + SC \tag{6.1}$$

where

- $MC$: Annual product recovery cost
- $RC$: Annual cost of delivering cores to remanufacturing facility
- $CC$: Annual amortized facility construction cost

- *OC*: Annual operating costs of remanufacturing facility
- *DC*: Annual cost associated with the redistribution of remanufactured products to consumers or retailers
- *SC*: Annual cost of selling remanufactured products

The following subsections present the detailed explanation of each component of the total cost equation.

### 6.3.1 Annual Product Recovery Cost

The annual product recovery cost is represented as follows:

$$MC = c_{pc} + c_{tr} + c_h \tag{6.2}$$

where $c_{pc}$ is the cost associated with the procurement of all cores, $c_{tr}$ represents transaction costs, and $c_h$ is the holding cost of cores. $c_{pc}$ and $c_{tr}$ can be calculated using the following equations:

$$c_{pc} = p. \ \frac{Q}{e_f} \tag{6.3}$$

$$c_h = \alpha_h. \ \frac{Q}{e_f} \ \cdot \alpha_p \cdot p \tag{6.4}$$

where $p$ is the purchase price of the core, $Q$ is the annual output of the remanufacturing facility, $e_f$ is the efficiency of remanufacturing operations (the ratio of remanufactured products to total number of cores received), $\alpha_h$ is the fraction of annual production volume held in inventory, and $\alpha_p$ is the cost factor (taken as 0.20 in this study, i.e., $\alpha_p \cdot p$ equals to 20% of the price of a core).

### 6.3.2 Annual Cost of Delivering Cores to Remanufacturing Facility

The following equation is used to determine the annual cost of delivering cores to the remanufacturing facility.

$$RC = \alpha_t \cdot l \cdot \frac{Q}{e_f \cdot \beta} \tag{6.5}$$

where $\alpha_t$ is the transportation cost rate, $\beta$ is the number of products per tonne (metric ton), and $l$ is the average delivery distance.

While determining $l$, it is assumed that the remanufacturing facility is located at the center of a circular service area with a radius of $r$. For uniformly distributed cores within this service area, the average delivery distance is $l = (2/3)\ r$.

The annual production rate of the remanufacturing facility determines the size of the service region. Therefore, we can determine $r$ as follows:

$$\delta \cdot \pi r^2 = \frac{Q}{e_f} \qquad r = \sqrt{\frac{Q/e_f}{\pi\delta}} \tag{6.6}$$

where $\delta$ is the product yield within the service area. Therefore, average delivery distance and annual delivery cost of cores can be written as

$$l = \frac{2}{3} \cdot \sqrt{\frac{Q}{\pi e_f \delta}} \tag{6.7}$$

$$RC = \frac{2}{3} \alpha_t \frac{Q}{e_f \cdot \beta} \sqrt{\frac{Q}{\pi e_f \delta}} \tag{6.8}$$

### 6.3.3 Annual Amortized Facility Construction Cost

Annual amortized facility construction cost is calculated using the following equation:

$$CC = \frac{c_{base}}{F} \cdot \left( \frac{Q/e_f}{Q_{base}} \right)^{\rho} \tag{6.9}$$

where $c_{base}$ is the construction cost of a baseline facility, $F$ is the life of the facility, $Q_{base}$ is the production capacity of a baseline facility, and $\rho$ is the economies of scale factor.

### 6.3.4 Annual Operating Costs of Remanufacturing Facility

The annual operating costs of the remanufacturing facility is given by

$$OC = o_{base} \cdot \left( \frac{Q/e_f}{Q_{base}} \right)^{\gamma} \tag{6.10}$$

where $o_{base}$ is the annual operating cost of the baseline facility and $\gamma$ is the scale factor for operation costs (this factor takes values between 0.5 and 1).

### 6.3.5 Annual Cost Associated with the Redistribution of Remanufactured Products to Consumers or Retailers

Assuming a same service area from which the cores are collected, we can determine the annual cost associated with the redistribution of remanufactured products to consumers or retailers using the following equation:

$$DC = \frac{2}{3}\alpha_t \frac{Q}{\beta}\sqrt{\frac{Q}{\pi e_f \delta}} \tag{6.11}$$

The only difference between this equation and Equation (6.8) is that, in this equation, the number of remanufactured products to be redelivered is reduced by the remanufacturing efficiency.

### 6.3.6 Annual Cost of Selling Remanufactured Products

The annual cost associated with the sale of remanufactured products can be determined as

$$SC = c_s \cdot Q \tag{6.12}$$

where $c_s$ is the transaction cost associated with the sale of a remanufactured product.

Putting all cost expressions so far explained into Equation (6.1), we get the following equation for total annual costs:

$$TC = p\ \frac{Q}{e_f}\ (1+\alpha_h\alpha_p) + c_{tr} + \frac{2}{3}\alpha_t \frac{Q}{e_f \cdot \beta}\sqrt{\frac{Q}{\pi e_f \delta}} + \frac{c_{base}}{F} \cdot \ \frac{Q\big/ e_f}{Q_{base}}^{\rho} + o_{base} \cdot \ \frac{Q\big/ e_f}{Q_{base}}^{\gamma}$$

$$+\frac{2}{3}\alpha_t \frac{Q}{\beta}\sqrt{\frac{Q}{\pi e_f \delta}} + c_s \cdot Q \tag{6.13}$$

While performing a cost-based evaluation of different alternatives, a more useful performance measure is the annual cost per remanufactured product, which can be determined by dividing the total annual costs by the number of products remanufactured annually. Therefore, the following equation can be used to determine the annual cost per remanufactured product:

$$UC = \frac{p}{e_f}(1+\alpha_h\alpha_p) + \frac{c_{tr}}{Q} + \frac{2}{3}\frac{\alpha_t}{\beta}\sqrt{\frac{Q}{\pi e_f \delta}}\ \ 1+\frac{1}{e_f}\ \ + \frac{c_{base}\cdot Q^{\rho-1}}{(e_f Q_{base})^{\rho}\cdot F} + \frac{o_{base}\cdot Q^{\gamma-1}}{(e_f Q_{base})^{\gamma}} + c_s \tag{6.14}$$

**TABLE 6.8**

Numerical Values of Parameters Used in the Numerical Example

| Parameter | Symbol | Numerical value | Unit |
|---|---|---|---|
| Purchase price of the core | $p$ | 2000 | $ |
| Order transaction costs | $c_{tr}$ | 10000 | $ |
| Efficiency of remanufacturing operations | $e_f$ | 0.80 | — |
| Fraction of annual production volume held in inventory | $\alpha_h$ | 0.20 | — |
| Cost factor | $\alpha_p$ | 0.20 | — |
| Transportation cost rate | $\alpha_t$ | 25 | — |
| Number of products per tonne | $\beta$ | 0.5 | — |
| Product yield within the service area | $\delta$ | 0.05 | units/km$^2$ |
| Construction cost of a baseline facility | $c_{base}$ | 15 | million |
| Life of the facility | $F$ | 12 | years |
| Production capacity of a baseline facility | $Q_{base}$ | 12000 | units |
| Economies of scale factor | $\rho$ | 0.8 | — |
| Annual operating cost of the baseline facility | $o_{base}$ | 3 | million |
| Scale factor for operation costs | $\gamma$ | 0.9 | — |
| Transaction cost associated with the sale of a remanufactured product | $c_s$ | 1200 | $/unit |

### 6.3.7 Numerical Example

The parameter values for the example are given in Table 6.8. Assuming an annual plant output of 20,000 units, total annual cost and annual cost per remanufactured product can be determined as follows:

$$TC = 2000\ \frac{20000}{0.80}\ (1 + 0.20\cdot 0.20) + 10000 + \frac{2}{3}25\frac{20000}{0.80\cdot 0.5}\sqrt{\frac{20000}{\pi\cdot 0.80\cdot 0.05}}$$

$$+\frac{15\cdot 10^6}{12}\cdot\left(\frac{20000/0.80}{12000}\right)^{0.8} + 3\cdot 10^6\cdot\left(\frac{20000/0.80}{12000}\right)^{0.9}$$

$$+\frac{2}{3}\cdot 25\cdot\frac{20000}{0.5}\sqrt{\frac{20000}{\pi\cdot 0.80\cdot 0.05}} + 1200\cdot 20000$$

$$TC = \ \$\,682,479,745.1$$

$$UC = \frac{682,479,745.1}{20000} = \$34,123.99$$

## 6.4 Other Models

Pochampally et al. (2003) propose a linear physical programming approach to identify potential recovery facilities. The total cost incurred by a recovery facility is defined as Class 1S. "Increment in quality of products at recovery facility," "the ratio of throughput of reprocessed products to supply of end-of-life products," "multiplication of throughput by disassembly time," and "customer service" are defined as Class 2S. Pochampally and Gupta (2005, 2008) use the analytic hierarchy process to identify the potential facilities in a set of candidate recovery facilities operating in the region where a reverse supply chain is planned to be established. The factors considered include average quality of used products, average supply of used products, average disassembly time of used products, customer service, and fixed cost of facility.

## 6.5 Conclusions

In this chapter, two models were presented for the evaluation of alternative remanufacturing facilities. In the first model, TOPSIS was used, while the second model was useful in helping a decision maker calculate the total cost associated with a remanufacturing facility. An overview of other models was presented in the previous section.

## References

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# Part III

# Planning Issues

# 7

# Forecasting

## 7.1 The Issue

Accurate forecasting of product returns is an important input in the analysis of remanufacturing systems. At the tactical level, these forecasts can be used in product acquisition management and capacity planning, and they are also required for various operational planning activities (viz., inventory management and production planning) (Toktay, 2003).

In this chapter we first analyze the use of classical forecasting techniques for estimating product returns. Then the forecasting methods presented by Kelle and Silver (1989) for returnable containers are illustrated with a numerical example. The last section presents an overview of various forecasting methodologies developed for the prediction of product returns.

## 7.2 Use of Classical Forecasting Techniques

In this section, we use two classical forecasting techniques (viz., moving averages and exponential smoothing) to predict product returns.

### 7.2.1 Moving Averages

A moving average of order $n$ is calculated by taking the mean of $n$ most recent observations. The following formula presents $F_t$, the forecast made in period $t$–1 for period $t$ (Nahmias, 1993).

$$F_t = \frac{1}{n} \cdot \sum_{i=t-n}^{i=t-1} R_i = \frac{1}{n} \cdot (R_{t-1} + R_{t-2} + \cdots + R_{t-n}) \tag{7.1}$$

where $R_i$ is the observed product return value in period $i$. According to this formula, we can easily state that the forecast for the next period is estimated as the arithmetic mean of the $n$ most recent observations.

### 7.2.2 Exponential Smoothing

Another popular forecasting technique is simple exponential smoothing, which uses the following equation:

$$F_t = \alpha \cdot R_{t-1} + (1 - \alpha) \cdot F_{t-1} \tag{7.2}$$

where $F_t$ and $F_{t-1}$ are the forecasts for periods $t$ and $t$–1, respectively; $R_{t-1}$ is the observed product return value in period $t$–1, and $0 \leq \alpha \leq 1$ is a smoothing constant. In this technique, the current observation of returns is weighted by $\alpha$, while past observations of returns are weighted by $(1- \alpha)$ (Nahmias, 1993).

### 7.2.3 Numerical Example

We present a numerical application to illustrate the use of moving averages and exponential smoothing in the prediction of return amounts. In Table 7.1, observed return data are given for 52 weeks. Using this data, we try to estimate the return amount for week 53. The 3-week moving average and exponential smoothing results are presented in Table 7.2. In the last row of this table, the forecasted values for week 53 can be seen. Both forecasting methods can only forecast one period ahead. The forecasted values for other future periods (week 54, 55 …) are assumed to be the same as for week 53. Figures 7.1 and 7.2 compare the actual and forecasted returns values using moving average and exponential smoothing techniques, respectively.

**TABLE 7.1**
Weekly Return Data

| Week | Returns | Week | Returns | Week | Returns | Week | Returns |
|---|---|---|---|---|---|---|---|
| 1 | 34 | 14 | 67 | 27 | 30 | 40 | 240 |
| 2 | 142 | 15 | 270 | 28 | 81 | 41 | 166 |
| 3 | 120 | 16 | 60 | 29 | 133 | 42 | 41 |
| 4 | 32 | 17 | 168 | 30 | 84 | 43 | 22 |
| 5 | 376 | 18 | 105 | 31 | 152 | 44 | 170 |
| 6 | 26 | 19 | 55 | 32 | 23 | 45 | 87 |
| 7 | 33 | 20 | 165 | 33 | 77 | 46 | 49 |
| 8 | 209 | 21 | 316 | 34 | 28 | 47 | 138 |
| 9 | 148 | 22 | 91 | 35 | 46 | 48 | 107 |
| 10 | 85 | 23 | 155 | 36 | 55 | 49 | 39 |
| 11 | 58 | 24 | 88 | 37 | 132 | 50 | 165 |
| 12 | 128 | 25 | 61 | 38 | 52 | 51 | 51 |
| 13 | 57 | 26 | 44 | 39 | 26 | 52 | 58 |

**TABLE 7.2**

3-Week Moving Average and Exponential Smoothing Estimates

| Week | 3-Week Moving Average | Exponential Smoothing (α = 0.2) |
|---|---|---|
| 1 | — | — |
| 2 | — | 34 |
| 3 | — | 120 |
| 4 | 99 | 120 |
| 5 | 98 | 49 |
| 6 | 176 | 311 |
| 7 | 145 | 83 |
| 8 | 145 | 43 |
| 9 | 89 | 176 |
| 10 | 130 | 154 |
| 11 | 147 | 98 |
| 12 | 97 | 66 |
| 13 | 90 | 115 |
| 14 | 81 | 68 |
| 15 | 84 | 67 |
| 16 | 131 | 229 |
| 17 | 132 | 94 |
| 18 | 166 | 153 |
| 19 | 111 | 115 |
| 20 | 109 | 67 |
| 21 | 108 | 145 |
| 22 | 178 | 282 |
| 23 | 191 | 129 |
| 24 | 187 | 150 |
| 25 | 111 | 100 |
| 26 | 101 | 69 |
| 27 | 64 | 49 |
| 28 | 45 | 34 |
| 29 | 51 | 71 |
| 30 | 81 | 121 |
| 31 | 99 | 91 |
| 32 | 123 | 140 |
| 33 | 86 | 47 |
| 34 | 84 | 71 |
| 35 | 42 | 36 |
| 36 | 50 | 44 |
| 37 | 43 | 53 |
| 38 | 78 | 116 |
| 39 | 80 | 64 |

(*continued*)

**TABLE 7.2 (CONTINUED)**

3-Week Moving Average and Exponential Smoothing Estimates

| Week | 3-Week Moving Average | Exponential Smoothing (α = 0.2) |
|---|---|---|
| 40 | 70 | 34 |
| 41 | 106 | 199 |
| 42 | 144 | 173 |
| 43 | 149 | 67 |
| 44 | 76 | 31 |
| 45 | 78 | 142 |
| 46 | 93 | 98 |
| 47 | 102 | 59 |
| 48 | 91 | 122 |
| 49 | 98 | 110 |
| 50 | 94 | 53 |
| 51 | 103 | 142 |
| 52 | 85 | 69 |
| **Forecast for week 53** | 91 | 60 |

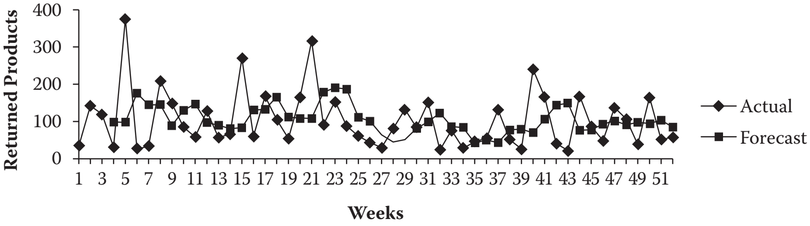

**FIGURE 7.1**
Actual and forecasted returns values using 3-week moving average.

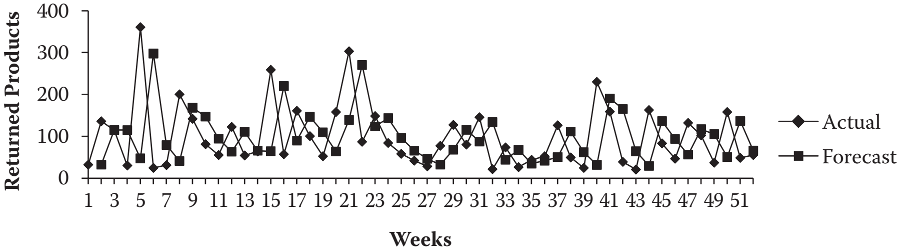

**FIGURE 7.2**
Actual and forecasted returns values using exponential smoothing.

## 7.3 A Family of Statistical Methods Developed for Product Returns

Kelle and Silver (1989) developed four forecasting methods with different information requirements to predict the container returns throughout the purchasing lead time. In this section we present the details of three of these methods using a numerical example. For this example, the observed values of containers issued and returns are given in Table 7.3. The probability of return in the first period is 0.2 (i.e., $p_1 = 0.2$), the probability of return in the second period is 0.5 (i.e., $p_2 = 0.5$), and the probability of return in the third period is 0.2 (i.e., $p_3 = 0.2$). The purchasing lead time is 2 weeks. Mean demand during the purchasing lead time is 50 containers. Standard deviation of the demand is 10. The actual period is 4 (i.e., $t = 4$).

### *METHOD 1*

This method assumes that there is an accompanying return of a reusable container associated with each demand. First, *P* (the probability that a container is ever returned) is calculated. Then the expected value (*ER*) and variance (*VR*) of lead time returns are calculated using the following formulas:

$$ER^{(1)} = P \cdot E(d_L) \tag{7.3}$$

$$VR^{(1)} = P^2 \cdot Var(d_L) + P \cdot (1 - P) \cdot E(d_L) \tag{7.4}$$

where $d_L$ is the random lead time demand, and $Var(d_L)$ is its variance. Using the foregoing numerical values, we can calculate the expected value and variance of lead time returns for our example as follows:

$$P = p_1 + p_2 + p_3 = 0.2 + 0.5 + 0.2 = 0.9$$

$$ER^{(1)} = 0.9 \cdot 50 = 45$$

$$VR^{(1)} = 0.9^2 \cdot 100 + 0.9 \cdot 0.1 \cdot 50 = 85.5$$

**TABLE 7.3**

Issues and Returns for Each Period

| Period | Issued | Returned 1 Period Later | Returned 2 Periods Later | Returned 3 Periods Later |
|---|---|---|---|---|
| 1 | 55 | 11 | 22 | 13 |
| 2 | 43 | 10 | 25 | — |
| 3 | 58 | 13 | — | — |
| 4 | 52 | — | — | — |

*METHOD 2*

More information is needed to implement this method. It requires the following two return data:

- The actual issues $u_i$ during each previous period $i \leq t$, where $t$ denotes the last period that we have observed (i.e., we are currently at the end of period $t$); and
- The probability distribution of the number of periods from issue to return for a container. The return probability after exactly $j$ periods is $p_j$. The return distribution $(p_1, p_2, \ldots, p_n, p_\infty)$ is an arbitrary discrete distribution. Returns of individually identified containers can be used to specify this distribution.

The expected value of lead time returns ($W_i$) from the previous issues ($u_i$) for $i \leq t$ is

$$ER_t^{(2)} = \sum_{i=1}^{t} E(W_i) = \sum_{i=i_m}^{t} u_i \cdot R_i(p_j\ s) \tag{7.5}$$

and variance

$$VR_t^{(2)} = \sum_{i=1}^{t} Var(W_i) = \sum_{i=i_m}^{t} u_i \cdot R_i(p_j\ s) \cdot [1 - R_i(p_j s)] \tag{7.6}$$

with

$$i_m = \max\{1, t - n + 1\} \tag{7.7}$$

since for $i < i_m$, $E(W_i) = 0$ and $Var(W_i) = 0$. $R_i = R_i(p_j{'}s)$ is a function of $i$ and the return distribution.

The expected value of lead time returns ($W_i$) from the lead time issues for $t < i \leq t + L - 1$ is

$$ER_L = \sum_{i=t+1}^{t+L-1} E(W_i) = \sum_{i=t+1}^{t+L-1} \quad_i \cdot R_i(p_j\ s) \tag{7.8}$$

$$VR_L = \sum_{i=t+1}^{t+L-1} Var(W_i) = \sum_{i=t+1}^{t+L-1} \{[\sigma_i \cdot R_i(p_j\ s)]^2 + \quad_i \cdot R_i(p_j\ s) \cdot [1 - R_i(p_j\ s)]\} \tag{7.9}$$

The forecast made by Method 2 for the total lead time return is the sum of the expected returns of previous issues and lead time issues.

$$ER^{(2)} = ER_t^{(2)} + ER_L \tag{7.10}$$

$$VR^{(2)} = VR_t^{(2)} + VR_L \tag{7.11}$$

Using the foregoing numerical values, we can calculate the expected value and variance of lead time returns for our example as follows:

$$E(W_2) = 43 * 0.2 = 8.6$$

$$Var(W_2) = 43 * 0.2 * (1 - 0.2) = 6.88$$

$$E(W_3) = 58 * (0.5 + 0.2) = 40.6$$

$$Var(W_3) = 58 * 0.7 * (1 - 0.7) = 12.18$$

$$E(W_4) = 52 * (0.2 + 0.5) = 36.4$$

$$Var(W_4) = 52 * 0.7 * (1 - 0.7) = 10.92$$

$$E(W_5) = 50 * 0.2 = 10$$

$$Var(W_5) = (10 \cdot 0.2)^2 + 50 \cdot 0.2 \cdot (1 - 0.2) = 12$$

$$ER^{(2)} = 8.6 + 40.6 + 36.4 + 10 = 95.6$$

$$VR^{(2)} = 6.88 + 12.18 + 10.92 + 12 = 41.98$$

### METHOD 3

In this method, it is assumed that each container is individually identified and a record is kept of when it is issued and returned. In addition to the two return data needed by Method 2, the following data are required.

- The amount of containers returned up to and including the present period $t$ ($V_i$) from each previous issue ($u_i$).

Using this additional information, the expected value and variance of returns during lead time are calculated as follows:

$$ER^{(3)} = \sum_{i=t_m}^{t-1} (u_i - V_i) \cdot Q_i(p_j\ s) + u_t \cdot R_t(p_j\ s) + ER_L \tag{7.12}$$

$$VR^{(3)} = \sum_{i=t_m}^{t-1} (u_i - V_i) \cdot Q_i(p_j\,'s) \cdot [1 - Q_i(p_j\ s)] + u_t \cdot R_t(p_j\ s) \cdot [1 - R_t(p_j\ s)] + VR_L \tag{7.13}$$

**TABLE 7.4**

Summary of Results

| Method | Expected Number of Returns | Variance of the Estimate |
|---|---|---|
| 1 | 45 | 85.5 |
| 2 | 95.6 | 41.98 |
| 3 | 91.11 | 29.62 |

with

$$Q_i(p_j\ s) = \frac{R_i(p_j\ s)}{1-\sum_{j=1}^{t-i} p_j} \tag{7.14}$$

Using the foregoing numerical values, we can calculate the expected value and variance of lead time returns for our example as follows:

$$Q_2(p_j\ s) = \frac{R_2(p_j\ s)}{1-\sum_{j=1}^{2} p_j} = \frac{p_3}{1-(p_1+p_2)} = \frac{0.2}{1-(0.2+0.5)} = \frac{0.2}{0.3} = \frac{2}{3}$$

$$Q_3(p_j\ s) = \frac{R_3(p_j\ s)}{1-\sum_{j=1}^{1} p_j} = \frac{(p_2+p_3)}{1-p_1} = \frac{(0.5+0.2)}{1-0.2} = \frac{0.7}{0.8} = \frac{7}{8}$$

$$ER^{(3)} = (43-35)\cdot\frac{2}{3} + (58-13)\cdot\frac{7}{8} + 36.4 + 10 = 91.11$$

$$VR^{(3)} = (43-35)\cdot\frac{2}{3}\cdot\ \ 1-\frac{2}{3}\ \ +(58-13)\cdot\frac{7}{8}\cdot\ \ 1-\frac{7}{8}\ \ + 10.92 + 12 = 29.62$$

Table 7.4 presents the expected number of returns and variance of the estimate for the three methods.

## 7.4 Other Models

The uncertainty in the timing and quantity of returns has forced researchers to develop alternative forecasting methods. Goh and Varaprasad (1986) developed the following transfer function model:

$$m_t = \frac{w_0 - w_1\cdot B - w_2\cdot B^2 - \cdots - w_s\cdot B^s}{1-\delta_1\cdot B - \delta_2\cdot B^2 - \cdots - \delta_r\cdot B^r}\cdot n_{t-b} + \varepsilon_t \tag{7.15}$$

where $m_t$ and $n_t$ are the returns and sales, respectively, in month $t$, $B$ is the backshift operator, $b$ is the time lag, $r$, $s$ are orders of the polynomials in the transfer function, $w_0, w_1, w_2, \ldots$, and $\delta_1, \delta_2, \ldots$ are coefficients to be estimated, and $\varepsilon_t$ is the noise term.

They also presented the same model in a different form as follows:

$$m_t = (\nu_0 + \nu_1 \cdot B + v_2 \cdot B^2 + \cdots) \cdot n_t + \varepsilon_t \tag{7.16}$$

The statistically significant values of $\nu_0, v_1, v_2, \ldots$ are used as estimates of return probability after $k$ periods ($k \geq 1$). Using this model, they estimated the returns of Coca-Cola bottles.

As an extension to Goh and Varaprasad (1986), Toktay et al. (2000) developed a Bayesian-estimation-based model by considering the augmentation of the data as new sales and return information becomes available. The following equation presents their model:

$$m_t = pr_D(1)n_{t-1} + pr_D(2)n_{t-2} + \cdots + pr_D(t-1)n_1 + \varepsilon_t \quad t = 2, 3, \ldots, \tag{7.17}$$

where $p$ is the probability that a product will ever be returned; $r_D(k)$ is the probability that the product will be returned after $k$ periods, conditional on ever being returned; and $\varepsilon_t$ $N$ (0, $\sigma^2$). The probability that a product will be returned in period $t + k$ provided that it was sold in period $t$ is $pr_D(k)$. The equation presented in equation 7.17 is a distributed lag model. Toktay et al. (2000) illustrated the proposed estimation procedure for a geometrically distributed lag.

de Brito and van der Laan (2009) and Toktay et al. (2004) investigate the performance of the forecasting methods proposed in Kelle and Silver (1989) by considering the impact of imperfect information on inventory-related costs.

The waste stream resulting from the disposal of CRTs in the United States for the period between 2000 and 2050 is estimated by Linton and Yeomans (2002), Linton et al. (2002), and Linton et al. (2005). First, a waste disposal model is developed in order to capture the uncertainty related with the television life cycle, the CRT weight in the televisions, the time between television failure and actual entrance time to the waste stream, and the proportion of televisions that are reclaimed. Then, Monte Carlo simulation is employed to estimate the future television sales considering three technological change scenarios: no technological change, moderate change, and aggressive change.

A fuzzy-logic-based approach is developed in Marx-Gomez et al. (2002) for the estimation of product returns. First, the data associated with return amounts, sales, and failures are generated using a simulation model. Then the return amounts are estimated for a specific planning period using a fuzzy inference system. Finally, the multiperiod forecasting of the return values is achieved by employing a neuro-fuzzy system.

## 7.5 Conclusions

Forecasting has utmost importance in the effective planning of a remanufacturing system. The success of capacity and production planning decisions are largely dependent on the accurate estimation of product returns. The high level of uncertainty associated with the timing and amount of returns has forced researchers to develop alternative forecasting methodologies. The majority of these models are based on mathematical modeling and/or simulation. In this chapter we investigated some of these methodologies. We also gave an overview of other studies in the previous section. Many of the methodologies have been developed by considering only one specific product-return scenario. The application of some of them requires extensive mathematical operations. There is a need for more research in this area in order to develop more general and practical forecasting methodologies.

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# 8

# Job Sequencing

## 8.1 The Issue

Job sequencing deals with the determination of the appropriate order in which waiting jobs should be served. Due to the combinatorial nature of sequencing problems, when the number of jobs is very large, the number of alternative job sequences also becomes very large. That is why numerous heuristic procedures have been developed for special case problems. There are also several priority sequencing rules (e.g., first in first out, last in first out, shortest processing time first, and longest processing time first) used in the assignment of jobs to one machine.

In this chapter we present a few heuristic procedures and priority sequencing rules that are applied to remanufacturing systems considering deterministic and stochastic processing times. Then, an overview of sequencing studies in remanufacturing is presented.

## 8.2 Adaptation of Classical Sequencing Rules to Remanufacturing

### 8.2.1 Deterministic Processing Times

#### *8.2.1.1 Case 1: n Jobs, One Machine*

This case involves $n$ jobs to be processed on one machine. While sequencing these jobs, an optimality criterion (e.g., mean flow time, earliness, and tardiness) is used. Here we take mean completion time as our optimality criterion in order to compare the performance of two simple sequencing rules, shortest processing time first (SPT), and longest processing time first (LPT). This criterion can be expressed as follows.

Table 8.1 presents the processing times of eight jobs. In Table 8.2, the sequence obtained by applying the SPT rule is presented with associated

**TABLE 8.1**

Processing Times of Jobs

| Job | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Processing time | 9 | 6 | 7 | 5 | 6 | 3 | 6 | 9 |

**TABLE 8.2**

Sequence of Jobs Obtained Using SPT Rule

| Job | 6 | 4 | 2 | 5 | 7 | 3 | 1 | 8 |
|---|---|---|---|---|---|---|---|---|
| Processing time | 3 | 5 | 6 | 6 | 6 | 7 | 9 | 9 |
| Completion time | 3 | 8 | 14 | 20 | 26 | 33 | 42 | 51 |

completion times for each job. The mean completion time for this sequence can be calculated as follows:

$$\text{Mean completion time} = (3 + 8 + 14 + 20 + 26 + 33 + 42 + 51)/8 = 24.63$$

In Table 8.3, the sequence obtained by applying the LPT rule is presented with associated completion times for each job. The mean completion time for this sequence can be calculated as follows:

$$\text{Mean completion time} = (9 + 18 + 25 + 31 + 37 + 43 + 48 + 51)/8 = 32.75$$

### *8.2.1.2 Case 2: n Jobs, Two Machines*

For this case, Johnson (1954) developed an algorithm based on the minimization of makespan (the time elapsed to complete all jobs). The algorithm provides an optimal solution and is valid if all jobs visit two machines in the same order (i.e., first Machine 1, then Machine 2). We can summarize the steps of Johnson's algorithm as follows (Elsayed and Boucher, 1994; Bedworth and Bailey, 1987):

1. Create a list of processing times of all jobs on machine 1 ($M_1$) and machine 2 ($M_2$).
2. Identify the shortest processing time in this list.
3. If the shortest processing time is on $M_1$, then assign the corresponding job to the next available position starting at the beginning of the

**TABLE 8.3**

Sequence of Jobs Obtained Using LPT rule

| Job | 8 | 1 | 3 | 7 | 5 | 2 | 4 | 6 |
|---|---|---|---|---|---|---|---|---|
| Processing time | 9 | 9 | 7 | 6 | 6 | 6 | 5 | 3 |
| Completion time | 9 | 18 | 25 | 31 | 37 | 43 | 48 | 51 |

**TABLE 8.4**

Processing Times of Jobs on Two Machines (in Minutes)

| Operation | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| First machine | 2 | 3 | 6 | 5 | 4 | 2 | 9 | 8 |
| Second machine | 1 | 2 | 5 | 3 | 5 | 6 | 5 | 4 |

sequence. Go to step 4. If it is on $M_2$, then assign the corresponding job to the next available position starting from the end of the sequence. Go to step 4.

4. Remove the assigned job from the list. Repeat steps 2 and 3 until all jobs are assigned.

If there is more than one job with the shortest processing time, the tie between them can be broken arbitrarily. The minimum elapsed time to complete all the jobs will not be affected by this decision.

The implementation of Johnson's algorithm is illustrated with a numerical example. Table 8.4 presents the processing times of jobs on two machines. The iterations of Johnson's algorithm can be seen in Figure 8.1. According to

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Iteration 1 | | | | | | | | 1 |
| Iteration 2 | 6 | | | | | | | 1 |
| Iteration 3 | 6 | | | | | | 2 | 1 |
| Iteration 4 | 6 | | | | | 4 | 2 | 1 |
| Iteration 5 | 6 | 5 | | | | 4 | 2 | 1 |
| Iteration 6 | 6 | 5 | | | 8 | 4 | 2 | 1 |
| Iteration 7 | 6 | 5 | | 7 | 8 | 4 | 2 | 1 |
| Iteration 8 | 6 | 5 | 3 | 7 | 8 | 4 | 2 | 1 |

**FIGURE 8.1**
The iterations of Johnson's algorithm.

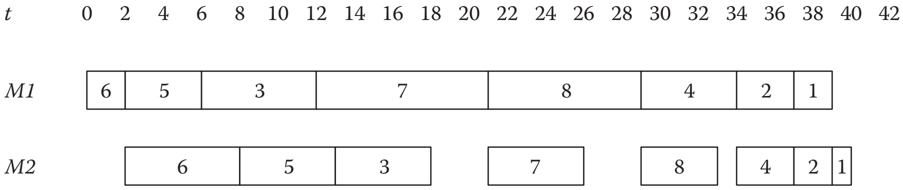

**FIGURE 8.2**
Gantt chart for the optimal sequence (two-machine case).

this figure, the optimal sequence is 6-5-3-7-8-4-2-1. This sequence results in a makespan of 40 minutes (see Figure 8.2).

### *8.2.1.3 Case 3: n Jobs, Three Machines*

Under certain conditions, Johnson's algorithm can be applied to a three-machine sequencing problem to obtain an optimal solution. These conditions are as follows:

- All jobs visit three machines in the same order (i.e., $M_1 - M_2 - M_3$).
- The minimum processing time of all jobs on either $M_1$ or $M_3$ is larger than the maximum processing time of all jobs on $M_2$.

If these conditions are satisfied, then two dummy machines are created to replace the three existing machines. The processing time of a job on $M_1'$ is calculated by summing its processing times on $M_1$ and $M_2$. The processing time of a job on $M_2'$ is calculated by summing its processing times on $M_2$ and $M_3$. The following example illustrates the use of Johnson's algorithm to a three-machine sequencing problem.

In a remanufacturing shop, six different jobs are subjected to processing operations on three different machines. The processing times of the jobs on each machine are given in Table 8.5. We want to determine the job sequence that will minimize the makespan.

**TABLE 8.5**
Processing Times of Jobs on Three Machines

| Job | First Machine ($M_1$) | Second Machine ($M_2$) | Third Machine ($M_3$) |
|---|---|---|---|
| 1 | 10 | 7 | 10 |
| 2 | 11 | 9 | 6 |
| 3 | 12 | 6 | 9 |
| 4 | 14 | 5 | 15 |
| 5 | 12 | 4 | 10 |
| 6 | 13 | 4 | 8 |

**TABLE 8.6**

Conversion of the Three-Machine Problem to a Two-Machine Problem

| Job | $M'_1$ ($M_1 + M_2$) | $M'_2$ ($M_2 + M_3$) |
|---|---|---|
| 1 | 17 | 17 |
| 2 | 20 | 15 |
| 3 | 18 | 15 |
| 4 | 19 | 20 |
| 5 | 16 | 14 |
| 6 | 17 | 12 |

Since minimum $M_1 = 10 > 9 =$ Maximum $M_2$, Johnson's algorithm can be applied by converting the three-machine problem to a two-machine problem (see Table 8.6).

The optimal sequence determined using Johnson's algorithm is 1-4-3-2-5-6. According to the Gantt chart presented in Figure 8.3, this sequence results in a makespan of 84 minutes.

### 8.2.2 Stochastic Processing Times

Simulation modeling is commonly used to evaluate the performance of alternative priority sequencing rules if the processing times are stochastic. This will be illustrated with the following numerical example.

We consider a remanufacturing shop that involves six work centers carrying out cleaning, refurbishing, and repair operations on disassembled components. In this shop, five part types are processed, each having two possible routes. The probability that a part type will follow a specific route and the means of exponentially distributed processing times (in minutes) at the work centers associated with a particular route can be seen in Table 8.7. Interarrival times for each part type are exponentially distributed with a mean of 28 minutes.

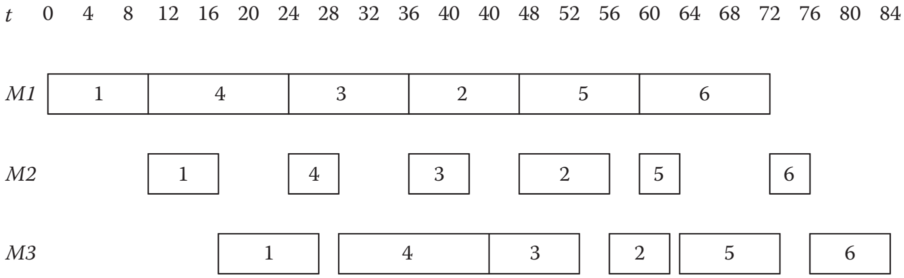

**FIGURE 8.3**
Gantt chart for the optimal sequence (3-machine case).

**TABLE 8.7**

Various Specifications for Each Route

| Route | Part | Work Center 1 | Work Center 2 | Work Center 3 | Work Center 4 | Work Center 5 | Work Center 6 | Probability |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 5 | 6 | — | — | 7 | 8 | 0.40 |
| 2 | 1 |  | 6 | — | 7 | — | 8 | 0.60 |
| 3 | 2 | 2 | — | 9 | — | 7 | 6 | 0.50 |
| 4 | 2 | 2 | — | 9 | — | 7 | — | 0.50 |
| 5 | 3 | — | — | — | 5 | 6 | 4 | 0.30 |
| 6 | 3 | — | — | — | — | 6 | 4 | 0.70 |
| 7 | 4 | — | — | 6 | — | 5 | 3 | 0.40 |
| 8 | 4 | — | — | 6 | — | 5 | — | 0.60 |
| 9 | 5 | 1 | — | — | — | 4 | 4 | 0.45 |
| 10 | 5 | 1 | — | — | — | — | 4 | 0.55 |

We evaluate the performance of the following sequencing rules:

1. Shortest processing time (SPT)
2. First in first out (FIFO)
3. Longest processing time (LPT)

In order to deal with the stochastic aspects of the system, we developed a simulation model using Arena 11 (Kelton et al., 2007). The performance measures used in the comparison of alternative sequencing rules were average flow time, $\mu_i$, for sequencing rule *i*, and work in process (WIP), $\beta_i$, for sequencing rule *i*. First, confidence intervals for $\mu_1 - \mu_2$, $\mu_1 - \mu_3$, and $\mu_2 - \mu_3$ were constructed with an overall confidence level of 95%. Then, confidence intervals for $\beta_1 - \beta_2$, $\beta_1 - \beta_3$, and $\beta_2 - \beta_3$ were constructed with an overall confidence level of 95%. The Bonferroni approach (see Banks et al., 2001) was used while constructing these multiple comparison confidence intervals.

Multiple comparison confidence intervals for average flow time are as follows:

$$-27.55 < \mu_1 - \mu_2 < -3.171$$
$$-69.69 < \mu_1 - \mu_3 < -45.31$$
$$-54.33 < \mu_2 - \mu_3 < -29.95$$

The confidence interval for $\mu_1 - \mu_2$ lies completely below zero, which provides strong evidence that $\mu_1 - \mu_2 < 0$. According to this information, sequencing rule 1 (SPT) is better than sequencing rule 2 (FIFO) since its average flow time is lower. Interpretation of the second confidence interval in a similar manner shows us that sequencing rule 1 is also better than sequencing rule 3 (LPT) based on average flow time.

Multiple comparison confidence intervals for WIP are as follows:

$-3.003 < \beta_1 - \beta_2 < -2.752$

$-10.7 < \beta_1 - \beta_3 < -10.45$

$-7.818 < \beta_2 - \beta_3 < -7.568$

The confidence interval for $\beta_1 - \beta_2$ lies completely below zero, which provides strong evidence that $\beta_1 - \beta_2 < 0$. According to this information, sequencing rule 1 (SPT) is better than sequencing rule 2 (FIFO) since its WIP is lower. Interpretation of the second confidence interval in a similar manner shows us that sequencing rule 1 is also better than sequencing rule 3 (LPT) based on WIP.

## 8.3 Other Models

Several remanufacturing-oriented sequencing and dispatching methodologies have been developed by researchers. Discrete event simulation (DES) is generally used to measure the performance of these methodologies. In Guide (1996), an MRP-based current production planning and control system is compared with a drum-buffer-rope (DBR)–based proposed system using DES modeling. The use of MRP in remanufacturing systems is criticized by stating that a remanufacturing environment characterized by a high level of uncertainty lacks the stability required by a successful MRP system. As an extension to Guide (1996), Guide (1997) tests the performance of priority dispatching rules in the DBR environment using DES. In Guide et al. (1997a), it is pointed out that faster flow times and a better delivery performance can be achieved by considering product structure in the selection of specific priority dispatching rules. A DES-based evaluation of order release strategies in a remanufacturing environment is presented by Guide and Srivastava (1997). Guide et al. (1997b) use DES modeling for the investigation of the disassembly release mechanisms and priority dispatching rules. In Guide et al. (1998), DES is used for the analysis of the effect of proactive expediting policies on various performance measures (viz., mean flow time, mean lateness, mean root mean square lateness, and mean percentage late). Guide et al. (1999) develop a DES model for the analysis of the impact of lead time variation on the performance of disassembly release mechanisms. The performance of several priority dispatching rules for a repair shop is evaluated using DES by Guide et al. (2000). The performance of static priority rules for a remanufacturing system involving shared facilities is evaluated by Guide et al. (2005).

Upon developing a network flow model to represent a remanufacturing flowshop, Stanfield et al. (2006) propose a structured heuristic approach that can develop sequences and ready times for remanufacturing systems by balancing three factors (viz., customer due dates, desired confidence levels, and stochastic makespan minimization).

## 8.4 Conclusions

In this chapter, sequencing of jobs on machines in a remanufacturing facility is presented. Several heuristics and priority rules from manufacturing literature are applied to the remanufacturing situation by considering deterministic as well as stochastic processing times for remanufacturing jobs. Finally, an overview of other remanufacturing-related sequencing models is presented in the previous section.

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# 9

# *Inventory Management*

## 9.1 The Issue

Traditional inventory models consider the characteristics of traditional manufacturing systems in which brand new parts are used to produce brand new products. They do not address the issues peculiar to product returns. Consideration of the product returns and remanufacturing options causes two additional complexities in traditional inventory management approaches (Inderfurth and van der Laan, 2001):

1. *Uncertainty associated with product returns*: Although producers have some tools (viz., incentives, discounts, buyback campaigns) to control product returns, quality, quantity, and timing of product returns are highly stochastic. Increasing safety stocks can be a natural solution to preventing backorders. However, this solution results in excessive holding costs. If the environmental legislation requires the producer to accept all product returns, it may end up receiving more product returns than it needs in remanufacturing operations. In that case, a viable solution alternative is the disposal of excess inventories, which increases disposal costs. In order to deal with these issues, inventory models developed for remanufacturing systems must have the ability to achieve trade-off among backorder, holding, and disposal costs.
2. *The need for coordination between the remanufacturing and regular mode of procurement*: In a typical remanufacturing system, serviceable inventory is fed by two sources: recovered parts from returned products and external procurement/production of parts. Joint consideration of these two sources lead to the following issues (Fleischmann et al., 1997):
    - The assumption that the inventory level for a component will always be decreasing between inventory replenishments is not valid due to the arrival of parts from remanufacturing.
    - There will be two different types of inventories: returned products inventory and serviceable inventory, forming a two-echelon system.

Researchers have developed various inventory models to deal with these complexities. In this chapter we review these models by considering various modeling approaches for demand and returns. The other inventory management issues including costs and valuation, effect of lead times, and spare part inventories are also covered in this chapter.

## 9.2 Use of EOQ Logic in Remanufacturing Inventory Management

The first model proposed by Gunter (2004) considers only the remanufactured components. The logic of the Economic Order Quantity (EOQ) model, a frequently used inventory model in manufacturing systems, is transferred to remanufacturing systems. The following assumptions are made in this model:

- There is complete disassembly of EOL products.
- There is no reactive disassembly.
- The disassembly rate remains fixed.
- There is a continuous and sufficient supply of EOL products.
- There is enough demand so that all retrieved parts can be absorbed. Thus, annual demand for a part equals its annual recovery rate.

Inventory models for a remanufacturing system dealing with the following three scenarios are considered here:

- Single Component
- Multiple Components with Equal Recovery Rates
- Multiple Components with Different Recovery Rates

### 9.2.1 Single Component

This case involves the disassembly and storage of only one component. The changes in inventory level in this model can be seen in Figure 9.1. According to this figure, recovery of a component is carried out at a constant rate, and recovered components are placed into storage. Upon reaching a predetermined inventory level, *S*, the inventory level is reduced to zero by selling all inventoried components.

The objective is to determine the optimum selling point based on the minimization of the total cost, which can be represented as follows:

$$TC = \frac{S}{2} \cdot H + \frac{D}{S} \cdot T \qquad (9.1)$$

where $S$ is the optimum selling point, $D$ is the annual demand, $H$ is the unit holding cost, $T$ is the transaction cost that is incurred with each sale (liquidation), $\frac{S}{2}$ is the average inventory level, $\frac{S}{2} \cdot H$ is the annual holding cost, $\frac{D}{S}$ is the number of inventory liquidations per year, and $\frac{D}{S} \cdot T$ is the annual transaction cost associated with the inventory liquidations.

The optimal selling point can be determined by differentiating $TC$ with respect $S$ and equating to zero:

$$\frac{dTC}{dS} = \frac{H}{2} - \frac{D \cdot T}{S^2} = 0$$

$S^*$ is determined by solving this equation as follows:

$$S^* = \sqrt{\frac{2 \cdot D \cdot T}{H}} \tag{9.2}$$

More useful information in this model is the time between inventory liquidations, $\tau$. Multiplication of $\tau$ by the number of liquidations per year ( $\frac{D}{S}$ ) is equal to 1 year (see Figure 9.1).

$$\tau \cdot \frac{D}{S} = 1$$

By putting the optimal selling point in this equation, the optimal time between inventory liquidations can be determined as follows:

$$\tau^* = \sqrt{\frac{2 \cdot T}{D \cdot H}} \tag{9.3}$$

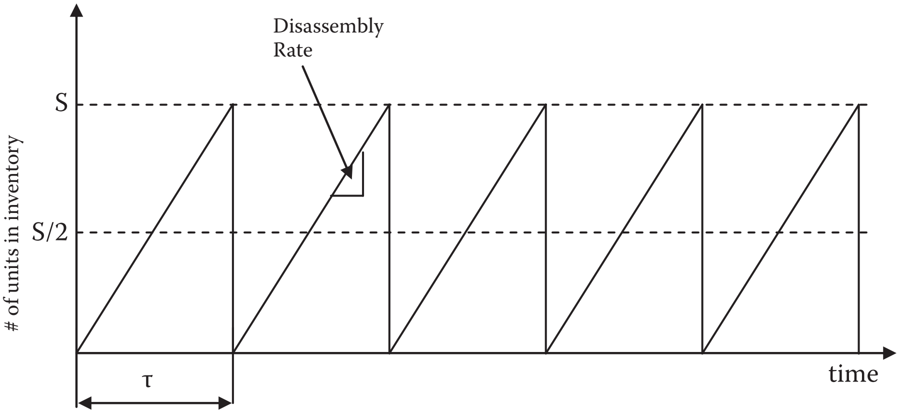

**FIGURE 9.1**
Inventory management with basic economic demanufacturing quantity model.

For the optimal selling point, the profit can be written as follows:

$$P = r \cdot D - \frac{D \cdot T}{S^*} - \frac{H}{2} \cdot S^* \tag{9.4}$$

where $r$ is the revenue per unit. By putting the expression for $S^*$ and simplifying, the profit expression can be written as follows:

$$P = r \cdot D - \sqrt{2 \cdot D \cdot T \cdot H} \tag{9.5}$$

#### 9.2.1.1 Numerical Example

The annual demand for a remanufactured part is 3000 units. The average annual unit holding cost is \$20, while the transaction cost is \$200. The revenue per unit is \$5. Using these data, $S^*$, $N$, $\tau^*$, and $P$ can be determined as follows:

$$\text{Optimum Selling Quantity} = S^* = \sqrt{\frac{2 \cdot 3000 \cdot 200}{20}} = 244.95 \simeq 245 \text{ parts}$$

$$\text{The number of inventory liquidations per year} = N = \frac{3000}{245} = 12.25$$

$$\text{The optimal time between liquidations (in years)} = \tau^* = \sqrt{\frac{2 \cdot 200}{3000 \cdot 20}} = 0.08165$$

$$\text{Profit} = P = 5 \cdot 3000 - \sqrt{2 \cdot 3000 \cdot 200 \cdot 20} = \$10101.2$$

### 9.2.2 Multiple Components with Equal Recovery Rates

Similar to the single component case, the objective in this case is the minimization of the total cost. For $n$ parts, the total cost can be represented as follows:

$$TC = \sum_{i=1}^{n} \frac{D}{S_i} \cdot T_i + \sum_{i=1}^{n} \frac{S_i}{2} \cdot H_i \tag{9.6}$$

The expression for the optimal selling point can be derived by differentiating this equation with respect to $S_i$ and equating to zero:

$$S_i^* = \sqrt{\frac{2DT_i}{H_i}} \tag{9.7}$$

In this case, an expression of the form "$F + D \cdot V$" (where $F$ is the total fixed cost and $V$ is the total variable cost) is used to include any operational cost together with the costs associated with the purchasing, transporting, and recovery of EOL products. Considering this cost structure, the total profit can be written as follows:

$$P = \sum_{i=1}^{n} R_i \cdot D - \sum_{i=1}^{n} \sqrt{2 \cdot D \cdot T_i \cdot H_i} - (F + D \cdot V) \tag{9.8}$$

where $R_i$ is the unit revenue for part $i$. After grouping similar terms, the resulting profit equation can be given as

$$\text{Profit} = \sum_{i=1}^{n} R_i - V \quad D - \sum_{i=1}^{n} \sqrt{2T_iH_i} \quad \sqrt{D} - F \tag{9.9}$$

#### 9.2.2.1 Numerical Example

In this example, the disassembly rate is equal to 3000 for all parts. Holding and transaction costs together with unit revenue values are given in Table 9.1. In addition to these data, total variable ($V$) and fixed costs ($F$) are \$20 and \$20,000, respectively.

Using the parameter values presented in Table 9.1, the optimal selling point for parts 1, 2, 3, 4, and 5 can be determined as 245, 173, 548, 258, and 173, respectively. Profit is calculated as follows:

$$\text{Profit} = ((5 + 10 + 12 + 8 + 20) - 20) \cdot 3000 - (\sqrt{2 \cdot 100 \cdot 10} + \sqrt{2 \cdot 75 \cdot 15}$$
$$+ \sqrt{2 \cdot 250 \cdot 5} + \sqrt{2 \cdot 200 \cdot 18} + \sqrt{2 \cdot 125 \cdot 25}) \cdot \sqrt{3000} - 20000 = \$68{,}236.11$$

### 9.2.3 Multiple Components with Different Recovery Rates

This scenario also considers multiple components. However, in this case, recovery rates of components are different due to the uncertainty associated

**TABLE 9.1**

Cost and Revenue Parameters for the Parts

| Part | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| $H_i$ | 10 | 15 | 5 | 18 | 25 |
| $T_i$ | 100 | 75 | 250 | 200 | 125 |
| $R_i$ | 5 | 10 | 12 | 8 | 20 |

with the condition of EOL products. The number of type *i* components recovered is given as

$$D_i = \eta_i \cdot D \tag{9.10}$$

where $D$ is the number of EOL products remanufactured per year, $D_i$ is the number of type *i* components recovered from $D$ EOL products, and $\eta_i$ is the fraction of recoverable parts.

The total cost function for this scenario can be written as follows:

$$TC = \sum_{i=1}^{n} \frac{D_i}{S_i} \cdot T_i + \sum_{i=1}^{n} \frac{S_i}{2} \cdot H_i + \frac{T_s}{S_s} \cdot \sum_{i=1}^{n} \psi_i \cdot (D - D_i) + \frac{S_s}{2} \cdot H_s \tag{9.11}$$

The first term in this function is the total annual transaction costs of components $i = 1$ to $n$. The second term is the total annual inventory holding costs of components $i = 1$ to $n$. The total annual transaction cost associated with the liquidation of the recyclable inventory is represented by the third term in the total cost function. According to this term, ($D$–$D_i$) number of parts that are not in good condition are stored in a bulk inventory. The components in this bulk inventory are recycled when the inventory level of this recyclable inventory reaches the selling point ($S_s$). The transaction and holding costs associated with this inventory are $T_s$ and $H_s$, respectively. $\psi_i$ is the mass-to-unit (or volume-to-unit) mapping conversion. The fourth term is the average annual holding cost of the recyclable inventory.

In order to determine the optimal selling point for component *i*, the partial derivative of *TC* with respect to $S_i$ is equated to zero and solved for $S_i$.

$$S_i^* = \sqrt{\frac{2D_iT_i}{H_i}} \tag{9.12}$$

The expression for the optimal time (in years) between inventory liquidations is

$$\tau_i^* = \sqrt{\frac{2T_i}{D_iH_i}} \tag{9.13}$$

In order to determine the optimal selling point for recyclable inventory, the partial derivative of *TC* with respect to $S_s$ is equated to zero and solved for $S_s$.

$$S_s^* = \sqrt{2\frac{T_s}{H_s} \sum_{i=1}^{n} \psi_i (D - D_i)} \tag{9.14}$$

The expression for the optimal time (in years) between liquidations of recyclable inventory is

$$\tau_s^* = \sqrt{\frac{2T_S}{H_S D \sum_{i=1}^{n} \psi_i (1-\eta_i)}} \tag{9.15}$$

The expression for the annual profit can be given as

$$\begin{aligned} P = & \sum_{i=1}^{n} R_i \cdot D_i \ + R_s \cdot \sum_{i=1}^{n} \psi_i \cdot (D - D_i) - (F + D \cdot V) \\ & - \sum_{i=1}^{n} \frac{D_i}{S_i^*} \cdot T_i + \sum_{i=1}^{n} \frac{S_i^*}{2} \cdot H_i + \frac{T_s}{S_s^*} \cdot \sum_{i=1}^{n} \psi_i \cdot (D - D_i) + \frac{S_s^*}{2} \cdot H_s \end{aligned} \tag{9.16}$$

where $R_i$ is the unit sales revenue of component $i$, and $R_s$ is the sales revenue from selling one unit of recyclable inventory.

Substitution of expressions into expression results in the following profit equation:

$$\begin{aligned} \text{Profit} = & \sum_{i=1}^{n} R_i \cdot \eta_i + R_S \sum_{i=1}^{n} \psi_i (1-\eta_i) - V \ . \\ D - & \sum_{i=1}^{n} \sqrt{2\eta_i T_i H_i} + \sqrt{2T_S H_S \sum_{i=1}^{n} \psi_i (1-\eta_i)} \ \sqrt{D} - F \end{aligned} \tag{9.17}$$

#### 9.2.3.1 Numerical Example

Here, the disassembly rate is equal to 4000 for all parts. The holding cost, transaction cost, revenue, mass-to-unit mapping conversion factor, and recovery yield for each part are given in Table 9.2. Total variable ($V$) and fixed

**TABLE 9.2**

Cost and Revenue Parameters for the Parts

| **Part** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| $H_i$ | 10 | 15 | 5 | 18 | 25 |
| $T_i$ | 100 | 75 | 250 | 200 | 125 |
| $R_i$ | 5 | 10 | 12 | 8 | 20 |
| $\Psi_i$ | 5 | 8 | 6 | 10 | 12 |
| $\eta_i$ | 0.70 | 0.80 | 0.65 | 0.75 | 0.90 |

**TABLE 9.3**

$S_i^*$ and $\tau_i^*$ values

| Part | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| $S_i^*$ | 237 | 179 | 510 | 258 | 190 |
| $\tau_i^*$ | 0.09 | 0.06 | 0.20 | 0.09 | 0.05 |

costs (*F*) are \$15 and \$18,000, respectively. The transaction and holding costs associated with recyclate are \$50/ and \$2/lb., respectively. The revenue from selling one pound scrap/recyclate is \$10.

The optimal selling point and the optimal time (in years) between inventory liquidations for each part were found using equations as can be seen in Table 9.3.

Optimum selling point for scrap/recycle inventory =

$$S_s^* =$$

$$\sqrt{\begin{array}{l}2\dfrac{50}{2}[5\cdot(4000-2800)+8\cdot(4000-3200)+6\cdot(4000-2600)+10\cdot(4000-3000)\\+12\cdot(4000-3600)]\end{array}}$$

$$S_s^* = 1334.17$$

$$\tau_s^* = \sqrt{\frac{2\cdot 50}{\begin{array}{l}2\cdot 4000\cdot[5\cdot(1-0.70)+8\cdot(1-0.80)+6\cdot(1-0.65)+10\cdot(1-0.75)\\+12\cdot(1-0.90)]\end{array}}}$$

$$\tau_s^* = 0.04$$

Profit = \$ 431,541.4

## 9.3 Joint Consideration of Manufacturing and Remanufacturing

In a model proposed by Teunter (2004), part remanufacturing and production of new parts are simultaneously considered. Considering the number of production and recovery lots in a cycle, there are many alternative policies. Formulas are developed for optimal production lot size and optimal recovery lot size considering two simple policies: (1, $N_r$) and ($N_p$, 1). In the (1, $N_r$) policy, one cycle involves one production lot and a fixed number ($N_r$) of recovery lots, while the ($N_p$, 1) policy cycle involves one recovery lot and a fixed number ($N_p$) of production lots.

For both policies, the following assumptions are made:

- Demand is continuous and deterministic.
- Return is continuous and deterministic.
- Demand rate is always positive (i.e., $D > 0$).
- Return rate is given as $F \cdot D$. In this expression, $F$ is the return fraction taking values between 0 and 1.
- Production rate is greater than demand rate.
- Recovery rate is greater than demand rate.
- All returned items are recovered.

### 9.3.1 (1, $N_r$) Policy

Figure 9.2 presents the inventory levels of serviceable and recoverable stocks in (1, $N_r$) policy as a function of time. According to this figure, the maximum stock of recoverables is equal to the number of returns during a period with $(1 - D/R) \cdot S_r + S_p$ demands. That is why the maximum level of recoverable stock is $F \cdot ((1 - D/R) \cdot S_r + S_p)$, and the average level of recoverable stock

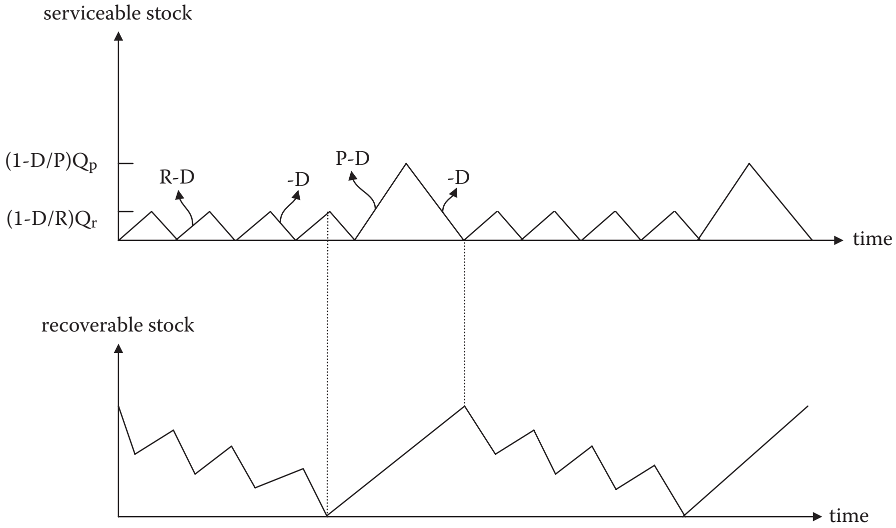

**FIGURE 9.2**
Serviceable and recoverable stock levels as a function time in (1, $N_r$) policy ($N_r = 4$ in this example).

is $\frac{1}{2}F\cdot((1-D/R)\cdot S_r + S_p)$, where $D$ is demand rate, $F$ *is* the return fraction, $R$ is recovery rate, $S_p$ is the lot size for production, and $S_r$ is the lot size for recovery.

Based on this information, the average holding cost associated with the recoverable stock can be written as follows:

$$C_1^{(1,N_r)} = H_r \cdot \frac{1}{2} \cdot F \cdot ((1-D/R)\cdot S_r + S_p) \tag{9.18}$$

where $H_r$ is holding cost per recoverable item.

Using the logic of traditional EOQ analysis, the average costs per time unit for ordering and for holding serviceable stock can be expressed for *production periods* as follows:

$$C_2^{(1,N_r)} = \frac{O_p \cdot D}{S_p} + H_s \cdot \frac{1}{2} \cdot (1-D/P)\cdot Q_p \tag{9.19}$$

while it can be expressed for *recovery periods* as follows:

$$C_3^{(1,N_r)} = \frac{O_r \cdot D}{S_r} + H_s \cdot \frac{1}{2} \cdot (1-D/R)\cdot Q_r \tag{9.20}$$

where $P$ is production rate, $O_p$ is the setup/ordering cost per production lot, $O_r$ is the setup/ordering cost per recovery lot, $H_s$ is holding cost per serviceable item, $Q_p$ is production lot size, and $Q_r$ is the recovery lot size.

Using the foregoing cost expressions, the total cost per time unit can be written as follows:

$$TC_{(S_p,S_r)}^{(1,N_r)} = C_1^{(1,N_r)} + (1-F)\cdot C_2^{(1,N_r)} + F\cdot C_3^{(1,N_r)} \tag{9.21}$$

$$\begin{aligned} TC_{(S_p,S_r)}^{(1,N_r)} = {} & H_r \cdot \frac{1}{2} \cdot F \cdot ((1-D/R)\cdot S_r + S_p) + \frac{O_p \cdot D \cdot (1-F)}{S_p} + \frac{O_r \cdot D \cdot F}{S_r} \\ & + H_s \cdot \frac{1}{2} \cdot ((1-F)\cdot(1-D/P)\cdot S_p + F\cdot(1-D/R)\cdot S_r) \end{aligned} \tag{9.22}$$

It must be noted that the total cost depends only on lot sizes. This is because $N_r$ is fully determined by lot sizes via the relation

$$N_r \cdot S_r \cdot (1-F) = S_p \cdot F \tag{9.23}$$

The choice of $S_p$ and $S_r$ is restricted by the foregoing relation since $N_r$ must be discrete. The lot sizing formulae are derived by ignoring this restriction. A procedure explained at the end of this section is used to modify the lot sizes in order to have a discrete $N_r$.

Taking the derivatives of Total Cost equation with respect to $S_p$ and $S_r$ and equating them to zero gives the following equations:

$$H_r \cdot \frac{1}{2} \cdot F - \frac{O_p \cdot D \cdot (1-F)}{S_p^2} + H_s \cdot \frac{1}{2} \cdot (1-F) \cdot (1-D/P) = 0 \tag{9.24}$$

and

$$H_r \cdot \frac{1}{2} \cdot F \cdot (1-D/R) - \frac{O_r \cdot D \cdot F}{S_r^2} + H_s \cdot \frac{1}{2} \cdot F \cdot (1-D/R) = 0 \tag{9.25}$$

Upon solving the foregoing equations, the optimal lot sizes are determined as follows:

$$S_p^{(1,N_r)} = \sqrt{\frac{2 \cdot O_p \cdot D \cdot (1-F)}{H_s \cdot (1-F) \cdot (1-D/P) + H_r \cdot F}} \tag{9.26}$$

$$S_r^{(1,N_r)} = \sqrt{\frac{2 \cdot O_r \cdot D}{(H_s + H_r) \cdot (1-D/R)}} \tag{9.27}$$

Employing Equation (9.23), $N_r$ can be expressed as follows:

$$N_r^{(1,N_r)} = \frac{S_p^{(1,N_r)} \cdot F}{S_r^{(1,N_r)} \cdot (1-F)} \tag{9.28}$$

In order to have a discrete $N_r$, $S_p^{(1,N_r)}$ is modified as follows:

$$\tilde{S}_p^{(1,N_r)} = \frac{\tilde{N}_r^{(1,N_r)} \cdot S_r^{(1,N_r)} \cdot (1-F)}{F} \tag{9.29}$$

where

$$\tilde{N}_r^{(1,N_r)} \cong \max\left\{1,\ N_r^{(1,N_r)}\ \right\} \tag{9.30}$$

is the positive integer nearest to $N_r^{(1,N_r)}$.

It must be noted that only $S_p^{(1,N_r)}$ is modified since the number of production lots is less than or equal to the number of recovery lots in (1, $N_r$) policy.

### 9.3.2 ($N_p$, 1) Policy

Figure 9.3 presents the inventory levels of serviceable and recoverable stocks in ($N_p$, 1) policy as a function of time. According to this figure, the average level of recoverable stock is $\frac{1}{2}\cdot(1-FD/R)\cdot S_r$. Following a procedure similar to the one presented in Section 9.3.1, the total cost per time unit can be written as follows:

$$TC_{(S_p,S_r)}^{(N_p,1)} = H_r \cdot \frac{1}{2} \cdot (1 - F \cdot D/R) \cdot S_r + \frac{O_p \cdot D \cdot (1-F)}{S_p} + \frac{O_r \cdot D \cdot F}{S_r} + H_s \cdot \frac{1}{2} \cdot ((1-F)\cdot(1-D/P)\cdot S_p + F \cdot (1-D/R)\cdot S_r) \tag{9.31}$$

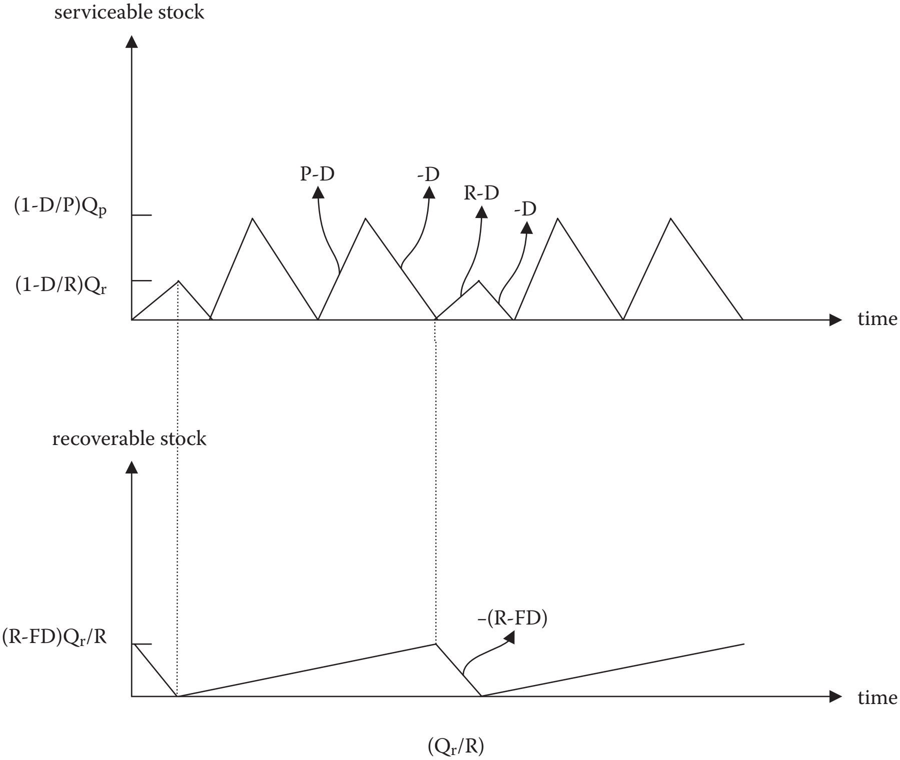

**FIGURE 9.3**
Serviceable and recoverable stock levels as a function time in ($N_P$,1) policy ($N_p$ = 2 in this example).

It must be noted that the total cost only depends on the lot sizes. This is because $N_p$ is fully determined by the lot sizes via the relation

$$S_r \cdot (1 - F) = N_p \cdot S_p \cdot F \tag{9.32}$$

The choice of $S_p$ and $S_r$ is restricted by the foregoing relation since $N_p$ must be discrete. The lot sizing formulae are derived by ignoring this restriction. A procedure explained at the end of this section is used to modify the lot sizes in order to have a discrete $N_p$.

Taking the derivatives of Equation (9.32) with respect to $S_p$ and $S_r$ and equating them to zero give the following equations:

$$-\frac{O_p \cdot D \cdot (1 - F)}{S_p^2} + H_s \cdot \frac{1}{2} \cdot (1 - F) \cdot (1 - D/P) = 0$$

and

$$H_r \cdot \frac{1}{2} \cdot (1 - F \cdot D/R) - \frac{O_r \cdot D \cdot F}{S_r^2} + H_s \cdot \frac{1}{2} \cdot F \cdot (1 - D/R) = 0$$

Solving these, we get the optimal lot sizes as follows:

$$S_p^{(N_p,1)} = \sqrt{\frac{2 \cdot O_p \cdot D \cdot (1 - F)}{H_s \cdot (1 - F) \cdot (1 - D/P)}} \tag{9.33}$$

$$S_r^{(N_p,1)} = \sqrt{\frac{2 \cdot O_r \cdot D \cdot F}{H_s \cdot F \cdot (1 - D/R) + H_r \cdot (1 - F \cdot D/R)}} \tag{9.34}$$

Employing Equation (9.32), $N_p$ can be expressed as follows:

$$N_p^{(N_p,1)} = \frac{S_r^{(N_p,1)} \cdot (1 - F)}{S_p^{(N_p,1)} \cdot F} \tag{9.35}$$

In order to have a discrete $N_p$, $S_r^{(N_p,1)}$ is modified as follows:

$$\tilde{S}_r^{(N_p,1)} = \frac{\tilde{N}_p^{(N_p,1)} \cdot S_p^{(N_p,1)} \cdot F}{(1 - F)} \tag{9.36}$$

**TABLE 9.4**

Parameter Values for the Numerical Example

| **Parameter** | **Value** |
|---|---|
| $D$ | 2000 |
| $F$ | 0.6 |
| $O_p$ | 30 |
| $O_r$ | 12 |
| $P$ | 8000 |
| $R$ | 6000 |
| $H_r$ | 4 |
| $H_s$ | 8 |

where

$$\tilde{N}_p^{(N_p,1)} \cong \max\left\{1,\ N_p^{(N_p,1)}\right\} \tag{9.37}$$

is the positive integer nearest to $N_p^{(N_p,1)}$.

It must be noted that only $S_r^{(N_p,1)}$ is modified since the number of recovery lots is less than or equal to the number of production lots in ($N_p$, 1) policy.

### 9.3.3 Numerical Example

A numerical example is provided in this section to demonstrate the use of the formulas presented earlier. Table 9.4 provides the parameter values for the example.

*FOR (1, $N_R$) POLICY:*

$$S_p^{(1,N_r)} = \sqrt{\frac{2\cdot 30\cdot 2000\cdot(1-0.6)}{8\cdot(1-0.6)\cdot(1-2000/8000)+4\cdot 0.6}} = 100$$

$$S_r^{(1,N_r)} = \sqrt{\frac{2\cdot 12\cdot 2000}{(8+4)\cdot(1-2000/6000)}} = 77.46$$

$$N_r^{(1,N_r)} = \frac{100\cdot 0.6}{77.46\cdot(1-0.6)} = 1.94$$

$$\begin{aligned} TC_{(S_p,S_r)}^{(1,N_r)} &= 4\cdot\frac{1}{2}\cdot 0.6\cdot((1-2000/6000)\cdot 77.46+100)+\frac{30\cdot 2000\cdot(1-0.6)}{100} \\ &+\frac{12\cdot 2000\cdot 0.6}{77.46}+8\cdot\frac{1}{2}\cdot((1-0.6)\cdot(1-2000/8000)\cdot 100 \\ &+0.6\cdot(1-2000/6000)\cdot 77.46) = \$\ 851.81 \end{aligned}$$

Since the value of $N_r^{(1,N_r)}$ is not an integer, it is rounded to $\tilde{N}_r^{(1,N_r)} = 2$.

Production lot size is modified as follows:

$$\tilde{S}_p^{(1,N_r)} = \frac{2 \cdot 77.46 \cdot (1 - 0.6)}{0.6} = 103.3$$

The corresponding total cost is \$ 852.06

*FOR ($N_p$, 1) POLICY:*

$$S_p^{(N_p,1)} = \sqrt{\frac{2 \cdot 30 \cdot 2000 \cdot (1 - 0.6)}{8 \cdot (1 - 0.6) \cdot (1 - 2000/8000)}} = 141.42$$

$$S_r^{(N_p,1)} = \sqrt{\frac{2 \cdot 12 \cdot 2000 \cdot 0.6}{8 \cdot 0.6 \cdot (1 - 2000/6000) + 4 \cdot (1 - 0.6 \cdot 2000/6000)}} = 67.08$$

$$N_p^{(N_p,1)} = \frac{67.08 \cdot (1 - 0.6)}{141.42 \cdot 0.6} = 0.32$$

$$\begin{aligned} TC_{(S_p,S_r)}^{(N_p,1)} &= 4 \cdot \frac{1}{2} \cdot (1 - 0.6 \cdot 2000/6000) \cdot 67.08 + \frac{30 \cdot 2000 \cdot (1 - 0.6)}{141.42} + \frac{12 \cdot 2000 \cdot 0.6}{67.08} \\ &\quad + 8 \cdot \frac{1}{2} \cdot ((1 - 0.6) \cdot (1 - 2000/8000) \cdot 141.42 + 0.6 \cdot (1 - 2000/6000) \cdot 67.08) \\ &= 768.74 \end{aligned}$$

Since the value of $N_p^{(N_p,1)}$ is not an integer, it is rounded to $\tilde{N}_p^{(N_p,1)} = 1$.

Recovery lot size is modified as follows:

$$\tilde{S}_r^{(N_p,1)} = \frac{1 \cdot 141.42 \cdot 0.6}{1 - 0.6} = 212.13$$

The corresponding total cost is \$1,086.11.

## 9.4 F-Policy Approach for Managing Inventory in a Remanufacturing System

Arrivals in a queuing system can be controlled using an F-Policy developed by Gupta (1995). In F-Policy, a single server finite capacity queuing system with Poisson customer arrivals (mean = $1/\lambda$) and exponential service times (mean = 1/ ) is considered. If the system reaches its capacity $K$ (i.e., the system becomes full), no further customers are allowed to enter the system until enough customers who are already in the system, have been served so that the number of customers in the system drops down to a threshold value of $F$ $(0 \leq F \leq K-1)$. At that point, a setup time is required to start allowing customers in the system which is exponentially distributed with mean $1/\beta$. From that point on, the system behaves normally until such time when it reaches its capacity, at which time the process is repeated all over again. Note that the customers not allowed in the queuing system are lost to the system.

### 9.4.1 Steady-State Solution

Let $p_{ij}$ where $(0 '' \; i'' \; K)$, and $(j = 0, 1)$ be the probability that there are $i$ customers in the system and the arrivals are either allowed $(j = 1)$ or not allowed $(j = 0)$ to enter the system. Thus (see Gupta, 1995),

$$p_{i0} = p_{00} \frac{1-\alpha}{\alpha^{i}} \quad 1 \leq i \leq F \tag{9.38}$$

$$p_{i0} = p_{00} \frac{1-\alpha}{\alpha^{F+1}} \quad F+1 \leq i \leq K \tag{9.39}$$

where $\alpha = \frac{}{+\beta}$

$$p_{i1} = p_{00} \frac{\sigma(1-\alpha)(1-\sigma^{K-i})}{(1-\sigma)\alpha^{F+1}} \quad F+1 \leq i \leq K-1 \tag{9.40}$$

$$p_{i1} = p_{00} \quad \frac{\sigma^{-i+F+2}(1-\alpha)^{2}}{(1-\sigma)(\sigma-\alpha)\alpha^{F+1}} - \frac{(1-\alpha)\sigma}{(\sigma-\alpha)\alpha^{i}} - \frac{\sigma^{K-i+1}(1-\alpha)}{(1-\sigma)\alpha^{F+1}} \qquad 0 \leq i \leq F \tag{9.41}$$

where $\sigma = \frac{}{\lambda}$

$$p_{00} = \quad \frac{(K-F-\sigma)(1-\alpha)}{(1-\sigma)\alpha^{F+1}} - \frac{1-\alpha^{F}\sigma}{(\sigma-\alpha)\alpha^{F-1}} - \frac{\sigma^{2}(1-\sigma^{K})(1-\alpha)}{(1-\sigma)^{2}\alpha^{F+1}} + \frac{\sigma^{2}(1-\sigma^{F+1})(1-\alpha)^{2}}{(1-\sigma)^{2}(\sigma-\alpha)\alpha^{F+1}} \quad {}^{-1} \tag{9.42}$$

### 9.4.2 System Performances

The expected number of parts in the system ($L$) is calculated using the following expression:

$$L = \sum_{i=0}^{K} i p_{i0} + \sum_{i=0}^{K-1} i p_{i1} \tag{9.43}$$

According to Little's Law, the following expression is used to determine the expected waiting time in the system (*W*):

$$W = \frac{L}{\lambda} \tag{9.44}$$

In Equation (9.44), $\lambda'$ is determined using the following expression:

$$\lambda \; = \lambda \sum_{i=0}^{K-1} p_{i1} \tag{9.45}$$

The expression for Total Cost (*TC (F,K)*) is as follows:

$$TC(F,K) = C_h \cdot L + C_{ins} \cdot p_e + C_{set} \cdot p_s + C_{lost} \cdot \lambda \cdot p_b + C_{wait} \cdot W + C_{fixed} \cdot K \tag{9.46}$$

where

$C_h$: Holding cost ($/part)
$C_{ins}$: Inspection cost ($/part)
$C_{set}$: Setup cost ($/part)
$C_{lost}$: Lost part (to system) cost ($/part)
$C_{wait}$: Waiting cost ($/part)
$C_{fixed}$: Fixed cost ($/part)
$P_e$: The probability that the workstation is providing inspection to the part
$P_s$: The probability that the server requires a startup time before starting again
$P_b$: The probability that the system is blocked (no entrance allowed)

In Equation (9.46), $p_e$, $p_s$, and $p_b$ values can be calculated as follows:

$$p_e = \sum_{i=0}^{K} p_{i0} + \sum_{i=0}^{K-1} p_{i1} \tag{9.47}$$

$$p_s = \sum_{i=0}^{F} p_{i0} \tag{9.48}$$

$$p_b = \sum_{i=0}^{K} p_{i0} \tag{9.49}$$

The F-Policy described can be used to control the inventory level of incoming EOL products. The following numerical example illustrates this idea.

### 9.4.3 Numerical Example

EOL products arrive at a collection facility according to the Poisson distribution with a rate of $\lambda = 2$. The inspection time for an EOL product follows an exponential distribution with a rate of $\ = 1$. The inspection setup time to start allowing EOL products in queue again is an exponential random variable with rate $\beta = 0.2$. The costs associated with the inventory process of EOL products are

$$C_h = \$1.5/product,\ C_{ins} = \$2.5/product,\ C_{set} = \$10/setup,\ C_{lost} = \$12/product,\ C_{wait} = \$9/product,\ C_{fixed} = \$2.5/product$$

If $F = 1$ and $K = 10$, various performance measures and total cost can be determined as follows:

$$L = \sum_{i=0}^{10} ip_{i0} + \sum_{i=0}^{9} ip_{i1} = 4.01$$

$$p_e = \sum_{i=0}^{10} p_{i0} + \sum_{i=0}^{9} p_{i1} = 1$$

$$p_s = \sum_{i=0}^{1} p_{i0} = 0.218$$

$$p_b = \sum_{i=0}^{10} p_{i0} = 0.611$$

$$\lambda\ = \lambda \cdot \sum_{i=0}^{9} p_{i1} = 0.78$$

$$W = \frac{L}{\lambda} = 5.15$$

$$TC(1,10) = 1.5 \cdot 4.01 + 2.5 \cdot 1 + 10 \cdot 0.22 + 12 \cdot 2 \cdot 0.61 + 9 \cdot 5.15 + 2.5 \cdot 10 = \$\ 83.69$$

## 9.5 Spare Parts Inventory Management Considering Remanufacturing

When a product reaches the end of its life cycle, its production is stopped. Manufacturers usually make a final order for the production or procurement of components before they stop production. This final order is used to meet the forecasted demand for spare parts throughout the postproduct life cycle

(PPLC). Besides the final order, disassembled components from the products collected from customers can be used to satisfy the demand. It must be noted that demand occurs due to repair and remanufacturing activities during PPLC. The following example illustrates the spare parts inventory management during PPLC considering repair, remanufacturing, and final order quantity (FOQ).

Consider a firm producing a seven-part product. Since the product has reached its end-of-production phase, the firm tries to determine the FOQs for three parts (A, D, E) of the product that are demanded most frequently. In addition to FOQ, the administration is planning to use disassembled parts from EOL products that arrive exponentially at a rate of 30 products per hour. The main demand source is the spare part need for repair and remanufacturing operations.

Table 9.5 depicts different parts disassembled at each station together with the mean disassembly times. Disassembly times for components are distributed exponentially. The order interarrival time is exponentially distributed with a mean of 5 minutes. There are seven order types. Some order types require the provision of more than one spare part type at the same time. The probability of occurrence of each order type and demand quantities for spare parts in each order type are depicted in Table 9.6. If the parts required by an order type could not be supplied using FOQ or disassembled parts, the order is lost.

According to the disassembly line control mechanism of the firm, if the FOQ for each part is greater than 10 (*minimum inventory level*), the incoming EOL products are not disassembled. They are stocked for disposal. Whenever the FOQ for a part reduces to a *minimum inventory level*, disassembly of this part is carried out. Disassembly of a part is stopped when the number of disassembled parts becomes equal to the difference between the *total expected demand during the PPLC* and the FOQ of this part. Following disassembly, the resulting subassembly is sent to the station, which disassembles a part

**TABLE 9.5**

Part Characteristics

| Part | Unit Production Cost (Final Order) | Unit Sales Price (Final Order) | Unit Sales Price (Disassembly) | Weight (lbs) | Volume (cft) | Station | Mean Disassembly Time (min) |
|---|---|---|---|---|---|---|---|
| A | 10 | 20 | 16 | 0.3 | 0.008 | 1 | 1 |
| B | — | — | — | 0.8 | 0.015 | — | — |
| C | — | — | — | 2 | 0.056 | — | — |
| D | 25 | 50 | 40 | 2 | 0.016 | 2 | 2 |
| E | 50 | 100 | 80 | 4 | 0.263 | 3 | 2 |
| F | — | — | — | 4 | 0.081 | — | — |
| G | — | — | — | 20 | 2.128 | — | — |

**TABLE 9.6**

Order Types

| Order Type | Probability | Spare Part Code | Demand Quantity | Probability |
|---|---|---|---|---|
| 1 | 0.20 | A | 1 | 0.60 |
| | | | 2 | 0.40 |
| 2 | 0.20 | D | 1 | 0.50 |
| | | | 2 | 0.50 |
| 3 | 0.20 | E | 1 | 0.80 |
| | | | 2 | 0.20 |
| 4 | 0.10 | A | 1 | 1 |
| | | D | 1 | 1 |
| 5 | 0.10 | A | 1 | 0.35 |
| | | | 2 | 0.65 |
| | | E | 1 | 0.40 |
| | | | 2 | 0.60 |
| 6 | 0.10 | D | 1 | 1 |
| | | E | 1 | 1 |
| 7 | 0.10 | A | 1 | 1 |
| | | D | 1 | 1 |
| | | E | 1 | 1 |

whose FOQ is less than or equal to the *minimum inventory level*. If there is no station in that condition, the subassembly is stocked for disposal. Whenever the total volume of the excess product and subassembly inventories become equal to the volume of a small truck (425 cft), the truck loaded with excess inventory is sent to a recycling facility. Any product or subassembly inventory that is greater than 10 *(maximum inventory level)* is assumed to be excess. Parts are disposed of at the end of the PPLC period. Part volumes are given in Table 9.5. The volume of a product is taken as 2.128 cft. In order to calculate the disposal cost of a product, subassembly, or part, the weight in pounds is multiplied by the *disposal cost per pound* ($0.4). Disposal costs of products and subassemblies are increased by a factor called the *disposal cost increase factor* (0.20). In the calculation of transportation cost, the operating cost associated with each trip of the truck is assumed to be $50. The disassembly cost is $2 per minute. For each EOL product, the facility demands a $30 collection fee.

A DES model of the system was developed using Arena 11 (Kelton et al., 2007). An animation of the DES model was built for the verification of the model. In addition, model output results were checked for reasonableness. Dynamic plots and counters providing dynamic visual feedback were used to validate the DES model. Each DES experiment has been carried out for 362,880 minutes, the equivalent of 3 years with one 8-hour shift per day.

In order to determine the *total expected demand during PPLC* for each part, five replications of the simulation model were carried out. The maximum total demand from these five replications was taken as the *total expected demand during the PPLC* value for the respective part.

### 9.5.1 GA Optimization Process

Each Genetic Algorithm (GA) chromosome represents a possible configuration of the FOQs of critical spare parts based on the specified upper and lower bounds. The GA performs tournament selection. The GA also uses elitism to save and copy the fittest chromosomes into the next generation. For each pair of selected parents, crossover and mutation operations are applied to generate a new pair of offspring. The two-point crossover is performed, and the crossover points are selected randomly. Since real-valued encoding is used in the GA, the mutation operator is implemented by random replacement. If a gene is to be mutated, a new FOQ is randomly picked and assigned to the gene. The following *Profit* function is employed to evaluate the fitness of each alternative solution:

$$Profit = (SR + CR) - (HC + DC + DPC + TC + FC) \tag{9.50}$$

The different cost and revenue components in Equation (9.47) can be defined as follows. *SR* is the revenue generated by component sales during the simulated time period (STP). *CR* is the revenue generated by the collection of EOL products during the STP. *HC* is the holding cost of parts, products, and subassemblies during the STP. *DC* is the disassembly cost during the STP. *DPC* is the disposal cost of parts, products, and subassemblies during the STP. *TC* is the transportation cost during the STP. *FC* is the total cost of final orders placed for three parts at the beginning of the PPLC.

The initial population is constructed by randomly creating a set of chromosomes. Each chromosome of the initial population is then evaluated by the DES model. The GA code automatically gets the fitness value of each alternative solution from the DES model to create a new generation using genetic operators. When the maximum number of generations is reached, the solution is accepted as optimal.

### 9.5.2 Results

GA uses a population size of 20, and 100 generations of evolution. The probability of crossover is set as 0.90. Mutation is performed immediately after the crossover with probability 0.10. For all parts, the lower bound is 0. The upper bound for each part is equal to the *total expected demand during PPLC*, that is, 47303, 43964, and 43934 for part A, D, and E, respectively. For each chromosome, five simulation replications were carried out.

The convergence graph of the GA is presented in Figure 9.4. According to this figure, the GA converges to a solution at the 51st iteration. The proposed

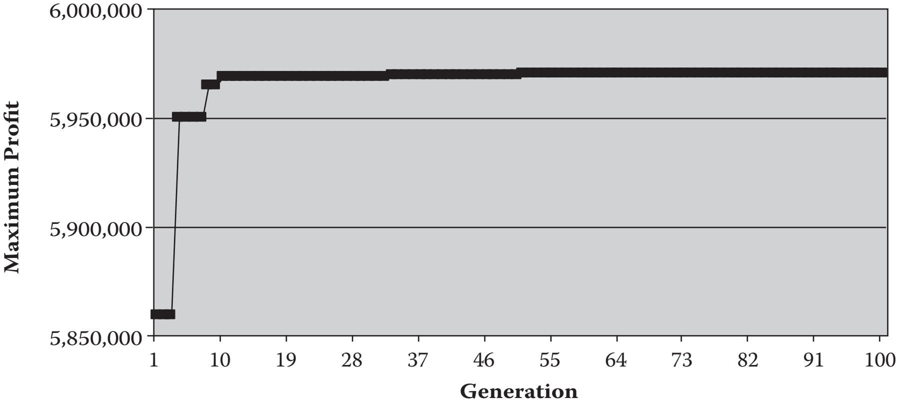

**FIGURE 9.4**
Convergence graph of the GA.

FOQs for part A, D, and E are 7247, 5828, and 3753, respectively. This solution results in an average profit of $5,970,125.

## 9.6 Other Models

Remanufacturing inventory models can be classified into two categories: deterministic models and stochastic models. Two subcategories can be distinguished in deterministic models considering the modeling of demand: stationary demand and dynamic demand. Stochastic models can be organized as periodic review and continuous review based on the review policy.

### 9.6.1 Deterministic Models

In these models, it is assumed that demand and return quantities are known for the entire planning horizon. Inventory policies are proposed by setting an optimal balance between fixed setup costs and variable inventory-holding costs.

### *9.6.1.1 Stationary Demand*

The logic of Economic Order Quantity (EOQ) (i.e., finding an optimal trade-off between fixed setup costs and variable inventory-holding costs) is exploited by deterministic models for the case of stationary demand (Fleischmann et al., 1997). Schrady (1967) presented the first EOQ model with item returns by assuming infinite production rates for manufacturing and remanufacturing.

Extending Schrady (1967), Nahmias and Rivera (1979) consider finite remanufacturing rates. Mabini et al. (1992) also extend Schrady by considering stockout service level constraints in a multiitem system. EOQ waste disposal and repair models with variable remanufacturing and return rates are presented by Richter (1996a, 1996b, 1997). Considering the different values of the return rate, these models can determine the optimal number of remanufacturing and production batches. The EOQ repair and waste disposal problem with integer setup numbers is analyzed by Richter and Dobos (1999) and Dobos and Richter (2000) using integer nonlinear models. The pure strategy (total repair or total waste disposal) is found to be optimal. A production-recycling system is investigated by Dobos and Richter (2003) for only one recycling lot and one production lot. These findings were generalized to multiple production and recycling lots by them (Dobos and Richter, 2004). In a follow-up study (Dobos and Richter (2006), their assumption of perfect quality of the returned items is relaxed. Extending Richter, (1996a, 1996b), El Saadany and Jaber (2008) consider the costs associated with switching between production and recovery runs. It is also emphasized that ignoring the first time interval causes an overestimation of holding costs due to an unnecessary residual inventory. Jaber and Rosen (2008) take the EOQ repair and waste disposal model of Richter (1996a, 1996b) and apply the first and second laws of thermodynamics to reduce system entropy. The possibility of lost sales was incorporated into the inventory models presented in Richter (1996a, 1996b) by Jaber and El Saadany (2009). As an extension to Dobos and Richter (2003, 2004), El Saadany and Jaber (2010) consider a price- and quality-dependant return rate. Learning effects in production and remanufacturing (repair) were incorporated into the model of Dobos and Richter (2003, 2004) by Jaber and El Saadany (2011).

EOQ formulas are developed in Teunter (2001) by using different holding cost rates for manufactured and recovered items. In the joint EOQ and EPQ model proposed by Koh et al. (2002), remanufacturing or procurement can be used to satisfy the stationary demand. As an extension to previous studies, a capacitated repair facility is considered. Extending Koh et al., Wee et al., (2006) develop a search procedure for the optimal ordering and recovery policy by allowing shortage backorders. The simple expressions developed by Teunter (2004) can determine the optimal lot sizes for the production/procurement of new items and for the recovery of returned items. These expressions are more general than those in the literature since they can be used for finite and infinite production rates as well as finite and infinite recovery rates. Konstantaras and Papachristos (2006) extend Teunter (2004) in two ways. First, they consider backordering. Second, they develop a mathematically rigorous approach leading to an overall optimal policy within a specific set of policies. Tang and Grubbström (2005) compare the performance of cycle order policy and dual sourcing ordering policy by considering stochastic lead times for manufacturing and remanufacturing. The optimal policy parameters for a recycling system in which returned items are used as raw material in the production of new products are developed by Oh and Hwang (2006).

Tang and Teunter (2006) formulate an MIP problem to find the cycle time and the production start times for (re)manufacturing lots based on the minimization of the total cost per time unit for a hybrid remanufacturing/manufacturing system in which manufacturing and remanufacturing operations for multiple product types are performed on the same production line. In a follow-up paper, the multiproduct economic lot scheduling problem is studied by Teunter et al. (2008) for the case of dedicated lines for manufacturing and remanufacturing. Teunter et al. (2009) develop simple and fast heuristics for the problem studied by Tang and Teunter (2006). Chung et al. (2008) simultaneously consider the concerns of the supplier, manufacturer, retailer, and third-party recycler while developing an optimal production and replenishment policy for a multiechelon inventory system with remanufacturing. They assume that a model cycle involves one manufacturing cycle and one remanufacturing cycle. Yuan and Gao (2009) extend Chung et al.'s (2008) model to the more general (1,$R$) (i.e., one manufacturing cycle and $R$ remanufacturing cycle) and ($P$, 1) (i.e., $P$ manufacturing cycle and one remanufacturing cycle) policies. In the hybrid remanufacturing–production system considered by Roy et al. (2009), defective units are continuously transferred to remanufacturing, and the constant demand is met by perfect items from production and remanufactured units. The rate of defectiveness of the production system is modeled as a fuzzy parameter, whereas the remanufactured units are treated as perfect items. The total number of cycles in the time horizon, the duration for which the defective items are collected, and the cycle length after the first cycle are determined using a GA based on the maximization of total profit. Rubio and Corominas (2008) determine the optimal values for manufacturing and remanufacturing capacities, return rates, and use rates for EOL products for a lean production–remanufacturing environment for which capacities of manufacturing and remanufacturing can be adjusted according to constant demand in order to prevent excessive inventory levels.

#### *9.6.1.2 Dynamic Demand*

In earlier studies, dynamic demand is handled by modifying the classical Wagner–Whitin algorithms, whereas DP-based algorithms are generally used in more recent studies. The extended Wagner–Whitin algorithm developed by Richter and Sombrutzki (2000) for a deterministic recovery system assumes a linear cost model with no backordering and negligible lead times. It is assumed that the quantity of used products matches the demand for remanufactured goods. That is why the model is applicable only to the case of a large quantity of used products. This model is extended by Richter and Weber (2001) by considering variable manufacturing and remanufacturing costs. An application of Richter and Sombrutzki's model in a just-in-time framework was presented by Richter and Gobsch (2003). In Minner and Kleber (2001), control theory is used to find an optimal policy for a remanufacturing system with dynamic demand by considering no backorders and lead times. Extending Minner and Kleber, Kiesmüller (2003a) determines an optimal policy for the case of positive and different lead times for production and remanufacturing. The lot-sizing problem with remanufacturing is modeled as a network flow problem in Golany et al. (2001). In a follow-up paper, a polynomial time algorithm is proposed for the case of concave costs by Yang et al. (2005). Pontryagin's Maximum Principle is used in Kleber et al. (2002) for the determination of the optimal policy by considering multiple remanufacturing options. However, they assume that no backorders are allowed and lead times are zero. Considering the dynamic lot-sizing problem with directly saleable returns, Beltran and Krass (2002) determine the manufacturing and disposal decisions by developing a DP algorithm with an $O(N^3)$ complexity for the case of concave costs. The dynamic lot-sizing problem with product returns and remanufacturing is studied by Teunter et al. (2006). They consider two scenarios for set up costs: a joint setup cost for manufacturing and remanufacturing (single production line) or separate setup costs (dedicated production lines). After modeling both problems as MIP programs, a DP algorithm is proposed for the joint setup cost setting. Modified versions of Silver Meal (SM), Least Unit Cost (LUC), and Part Period Balancing (PPB) heuristics are also provided for both settings. Pan et al. (2009) develop dynamic-programming-based algorithms for the capacitated dynamic lot sizing problem with product returns and remanufacturing. The optimal policy proposed by Konstantaras and Papachristos (2007) specifies the period of switching from remanufacturing to manufacturing, the periods where remanufacturing and manufacturing activities take place, and the corresponding lot sizes. A production–remanufacturing control problem is investigated by Bera et al. (2008) by assuming that product defectiveness is stochastic, and the upper bounds for production, remanufacturing, and disposal are fuzzy.

### 9.6.2 Stochastic Models

Demand and returns are modeled using stochastic processes in stochastic models. There are two commonly used stochastic models: the continuous review model and the periodic review model.

#### *9.6.2.1 Continuous Review Models*

In these models, the optimal static control policies are determined based on minimization of the long-run average costs per unit of time using continuous time axis (Fleischmann et al., 1997). A continuous review strategy for a single-item inventory system with remanufacturing and disposal is proposed by Heyman (1977). An optimum disposal level is determined with the assumption of no fixed ordering costs and instantaneous outside procurement. Extending Heyman, Muckstadt and Isaac (1981) develop a model involving nonzero lead times for repair and procurement and nonzero fixed costs. However, they develop an approximate numerical procedure to determine the optimal parameter values by ignoring disposal of the products. As an extension to Muckstadt and Isaac, van der Laan et al. (1996a, 1996b) consider a disposal option and compare a number of policies numerically. Considering this setting, van der Laan and Salomon (1997) and van der Laan et al. (1999b) present a detailed analysis of different policies to control serviceable and recoverable stock based on nonzero lead times for both sources. Two policies are mainly considered: a push-and-pull-driven recovery policy. As an extension to van der Laan et al. (1999b), stochastic lead times for manufacturing and remanufacturing are considered in another van der Laan et al. (1999a). The parameters of a (*s*, *Q*) policy for a basic inventory model involving Poisson demand and returns are optimized by Fleischmann et al. (2002). In Fleischmann and Kuik (2003), an average cost optimal (*s*, *S*) policy for an inventory system involving independent stochastic demand and item returns is developed using general results on Markov decision processes. Using certain extensions of the (*s*, *Q*) policy and assuming the equality of manufacturing and remanufacturing lead times, van der Laan and Teunter (2006) propose closed-form expressions for each policy to calculate near-optimal policy parameters. In Zanoni et al. (2006), some inventory control policies extended from the traditional inventory control models such as (*s*, *Q*) and (*s*, *S*) are analyzed for a hybrid manufacturing/remanufacturing system with stochastic demand, return rate, and lead times. DES is used to compare different inventory control policies based on the total cost. Planning the stability of production and remanufacturing setups in a product recovery system is studied by Heisig and Fleischmann (2001). Priority decision between manufacturing and remanufacturing is taken based on an average cost comparison in the foregoing models. In Aras et al. (2006), the reliability of this technique is questioned, and two alternative strategies that use either manufacturing or remanufacturing as the primary source to satisfy demand are developed.

A queuing network model is used to analyze the behavior of a multiechelon inventory system with returns in Korugan and Gupta (1998). Toktay et al. (2000) investigate the procurement of new components for recyclable products by developing a closed queuing network model. A queuing network model involving manufacturing/remanufacturing operations, supplier's operations for the new parts, and useful lifetime of the product is presented in Bayindir et al. (2003). The conditions on different system parameters (such as lifetime of the product, supplier lead time, lead time and value added of manufacturing and remanufacturing operations, capacity of the production facilities) that make the remanufacturing alternative attractive are investigated using this model based on the total cost. A closed-form solution is developed by Ching et al. (2003) for the system steady-state probability distribution for an inventory model with returns and lateral transshipments between inventory systems. The behavior of stochastic remanufacturing systems is analyzed by Nakashima et al. (2002) and Nakashima et al. (2004) by developing Markov chain models. A Markov chain model is developed by Takahashi et al. (2007) to analyze the performance of the alternative policies proposed for a recovery system decomposing recovered products into parts, materials, and waste.

#### *9.6.2.2 Periodic Review Models*

The optimal policy is determined based on the minimization of expected costs over a finite planning horizon in these models (Fleischmann et al., 1997). The optimal policy proposed by Simpson (1978) involves three parameters ($S$, $M$, $U$), where $S$ is produce-up-to level, $M$ is remanufacture-up-to-level, and $U$ is the dispose-down-to level. A disposal option and zero lead times are the main assumptions of this model. Inderfurth (1997) extends Simpson's model by considering nonzero lead times. He shows the optimality of the ($S$, $M$, $U$) policy for the case of equal lead times. An exact computation method and two approximations are provided by Kiesmüller and Scherer (2003) to determine the optimal parameter values for the periodic review policy studied by Simpson (1978) and Inderfurth (1997). Assuming that all available recoverables can be remanufactured, Mahadevan et al. (2003) develop heuristics to determine only produce-up-to level for a pull policy. Simple expressions proposed by Kiesmüller (2003b) and Kiesmüller and Minner (2003) allow for the calculation of the produce-up-to level and the remanufacture-up-to level for the cases of identical and nonidentical lead times. Ahiska and King (2010) extend Kiesmüller (2003b), Kiesmüller and Minner (2003), and Kiesmüller and Scherer (2003) by considering setup costs and different lead time cases for manufacturing and remanufacturing. Inderfurth et al. (2001) determine the optimal policy parameters of a stochastic remanufacturing system with multiple reuse options using an approximation algorithm.

In some studies, multiechelon systems are considered. The model studied by Simpson (1978) and Inderfurth (1997) is extended to a series system with no disposal in DeCroix (2006). The optimality of an echelon base-stock policy is shown by DeCroix et al. (2005) considering an infinite-horizon series system where returns go directly to stock. A similar analysis is carried out by DeCroix and Zipkin (2005) for an assembly system.

A special case of periodic review models with only one period is the newsboy problem (Dong et al. (2005). Returns are incorporated into the classical newsboy problem in Vlachos and Dekker (2003) and Mostard and Teunter (2006). Determination of the initial order quantity is the main aim in these studies. In Vlachos and Dekker (2003), it is assumed that a constant portion of the sold products is returned and that products can be resold at the most once. In the newsboy problem presented in Vlachos and Dekker (2003), a sold product is returned with a certain probability, and it can be sold as long as there is no damage to it.

### 9.6.3 Costs and Valuation

Several studies have been reported on the valuation of inventory and the investigation of the effect of different holding cost setting rules on the performance of a remanufacturing system. Teunter et al. (2000) present a simulation-based evaluation of the performance of alternative rules to set the inventory-holding cost rates for a continuous review model with stochastic demand and return of items and fixed positive lead times for manufacturing and remanufacturing. Teunter and van der Laan (2002) show that the Average Cost (AC) approach may not always be appropriate for a deterministic RL inventory model with both remanufacturing and disposal of returned products. Considering the stochastic version of the same problem, van der Laan (2003) compares Net Present Value (NPV) and AC rules using an exact procedure rather than simulation. In Corbacioglu and van der Laan (2007), it is emphasized that correct holding cost rates are different from the traditional valuation methodology. The impact of this finding on the operational performance of a two-product two-source remanufacturing environment is also evaluated. The effect of different inventory-holding cost setting rules on the performance of a disassembly and recovery system is studied by Akcali and Bayindir (2008). In Tang et al. (2004), the values of the return products are calculated using an MRP theory and decision-analysis-based methodology. Then, the inventory-holding costs are estimated based on these values.

### 9.6.4 Effect of Lead Time

Investigation of the impact of manufacturing, procurement, and remanufacturing lead times on the performance of inventory control policies is another important inventory management issue. Inderfurth (1997) considers lead times for procurement and remanufacturing while developing DP-based simple optimal replenishment and disposal policies for a stochastic product recovery system. He emphasizes that derivation of optimal decision rules is possible as long as the difference between lead times is at the most one period. A numerical analysis of the effects of lead time duration and lead time variability on total expected costs in production/inventory systems with remanufacturing is provided by van der Laan et al. (1999a). In van der Laan et al. (1999b), the effect of lead times is analyzed by assuming a deterministic manufacturing lead time and a deterministic remanufacturing lead time, rather than a deterministic manufacturing lead time and stochastic remanufacturing lead time resulting from limited remanufacturing capacity. In the remanufacturing system considered by Inderfurth and van der Laan (2001), lead times for remanufacturing and regular procurement differ. In order to analyze this system, they first define lead time as a decision variable. Then, a DP approach is developed to investigate the effect of lead time. The impact of shorter supplier lead times on manufacturing costs is analyzed by Ferrer (2003) and Ferrer and Ketzenberg (2004). The effect of manufacturing and remanufacturing lead times on the optimal parameter value and total cost is investigated by Mahadevan et al. (2003). Strategies for hybrid manufacturing/remanufacturing systems with long manufacturing lead times and short remanufacturing lead times are proposed in Teunter et al. (2004). Tang and Naim (2004), Zhou et al. (2006), and Zhou and Disney (2006) analyze the effect of manufacturing/remanufacturing lead time on system performance using control theory and simulation. Assuming a normally distributed lead time, Tang et al. (2007) estimate the planned lead time in a manufacture-to-order remanufacturing environment. The normality assumption of Tang et al. (2007) is questioned by Bao et al. (2008). They approximate the lead time distribution using the Minimum Relative Entropy (MRE) method which provides a better approximation than the normal approximation.

### 9.6.5 Inventory Substitution

Substitution between manufactured and remanufactured products is possible in some remanufacturing inventory models. In the hybrid manufacturing/remanufacturing systems analyzed by Inderfurth (2004) and Bayindir et al. (2005), there is a significant difference between the remanufactured and new products, and a new product can be offered as a substitute to the remanufactured product in case of shortage of a remanufactured product. A continuous-review (S-1, S) inventory control policy is developed for both types of products. These two studies are extended by Bayindir et al. (2007) considering a finite production capacity. Based on the assumptions of deterministic demand and return quantities and uncapacitated production, Yongjian et al. (2006) develop a DP-based approximate solution procedure to obtain near-optimal solutions for the problem with multiple product types and multiple periods.

### 9.6.6 Spare Parts Inventories

Researchers developed several spare parts inventory management models by considering the recovered parts from EOL products as a source of spare parts supply. Fleischmann et al. (2003) use a basic analytic inventory model and a simulation model to test alternative policies based on alternative channel designs and alternative coordination mechanisms by considering the use of disassembly as a source of spare parts in a case study conducted in IBM. SDS modeling is used by Spengler and Schroeter (2003) and Schroter and Spengler (2004) to evaluate various spare part acquisition alternatives for electronic equipment in EOL phase. An integrated approach considering various spare part acquisition alternatives is developed by Inderfurth and Mukherjee (2008). First, the underlying decision problem is structured, and the interdependencies of different alternatives to choose are demonstrated using a decision tree. Then parameters of a simple order-up-to policy are determined using simple decision rules and a heuristic solution procedure developed based on stochastic DP. Ilgin and Gupta (2008b) consider only the parts recovered from discarded EOL products as a source of spare parts during the postproduct life cycle, while developing a GA-based simulation-optimization methodology to determine the optimal final order quantities for a number of spare parts. Ilgin and Gupta (2008a) simultaneously consider two spare parts acquisition alternatives (viz., recovered PCBs from EOL TVs and newly purchased PCBs) in order to determine the optimum reorder and order quantity levels for the spare Printed Circuit Boards (PCBs) using simulation optimization.

## 9.7 Conclusions

In this chapter, four categories of models were presented for inventory management in remanufacturing systems. The first category transfers the EOQ logic to remanufacturing inventory management, while the second category develops optimal inventory policies considering both manufacturing and remanufacturing. The third category made use of queuing theory to control remanufacturing inventory. Finally, the fourth category presented an integrated approach involving simulation and genetic algorithm for the spare parts inventory management in remanufacturing systems. An overview of remanufacturing inventory models was provided in the previous section.

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# 10

# *Production Planning and Control*

## 10.1 The Issue

The production planning function in remanufacturing is responsible for planning how much and when to disassemble, how much and when to remanufacture, how much to produce and/or order for new materials, as well as coordinating disassembly and reassembly. Production planning in remanufacturing is more complicated than in a traditional manufacturing system due to the high level of uncertainty associated with the condition, quantity, and arrival time of product returns—the main input to a remanufacturing system. In a manufacturing system, the quality of inputs (i.e., materials and/or components) is homogenous since they are provided by the suppliers of the company under strict quality requirements. However, used products are returned by consumers who do not have any responsibility or concern about the condition of the product. This nonhomogenous structure of product returns makes lead times of remanufacturing operations very erratic. In addition, forecasts are less accurate since the number of product returns shows wide variation from period to period.

In order to deal with these complications, researchers have developed various production planning methodologies for remanufacturing. Some of these methodologies employ mathematical programming to obtain an optimum production plan, while some others use simulation to analyze the production planning decisions. Another category involves studies adapting traditional production planning and control methods such as MRP to remanufacturing systems. In this chapter, first, we investigate three MRP-based remanufacturing methodologies. Then we present an overview of other methodologies.

## 10.2 Production Planning for Product Remanufacturing

Souza (2010) developed a Material Requirements Planning (MRP)–based production planning method for remanufacturing. The main idea of the method

**TABLE 10.1**

Forecasted and Actual Demand for Product Returns

| Week | Forecasted Demand (FD) | Actual Demand (AD) | AD/FD Ratio |
|---|---|---|---|
| 1 | 175 | 192 | 1.097 |
| 2 | 150 | 137 | 0.913 |
| 3 | 225 | 243 | 1.08 |
| 4 | 200 | 213 | 1.065 |
| 5 | 325 | 301 | 0.926 |
| 6 | 165 | 174 | 1.055 |
| 7 | 300 | 287 | 0.957 |
| 8 | 310 | 323 | 1.042 |
| 9 | 225 | 243 | 1.08 |
| 10 | 300 | 279 | 0.93 |
| 11 | 180 | 192 | 1.067 |
| 12 | 255 | 272 | 1.067 |
| 13 | 295 | 317 | 1.075 |
| 14 | 275 | 255 | 0.927 |
| 15 | 150 | 134 | 0.893 |
| 16 | 180 | 197 | 1.094 |
| 17 | 200 | 213 | 1.065 |
| 18 | 325 | 309 | 0.951 |
| 19 | 190 | 203 | 1.068 |
| 20 | 170 | 157 | 0.924 |
| 21 | 200 | 221 | 1.105 |
| 22 | 220 | 199 | 0.905 |
| 23 | 185 | 173 | 0.935 |
| 24 | 145 | 168 | 1.159 |
| **Average** | | | **1.016** |
| **Std. dev.** | | | **0.081** |

is to develop a schedule for the remanufacturing of a particular product. We explain the logic of this methodology using the following example.

Consider a firm trying to determine how many units of a particular product should be remanufactured for an 8-week planning horizon. It has records of forecasted demand (FD) and actual demand (AD) for the past 24 weeks (see Table 10.1). An important input for the method is the AD/FD ratio, which is used as a measure of forecast uncertainty. The AD/FD ratio for each week, average, and standard deviation($StdDev_{AD/FD}$) of weekly AD/FD ratios are also provided in Table 10.1. Before implementing the MRP logic, the fluctuating safety stock values are created for each future week using $StdDev_{AD/FD}$ as follows:

$$\text{SS factor} = 1 + s \cdot StdDev_{A/F} \tag{10.1}$$

In this equation, *s* is a safety factor that is calculated considering the underordering ($C_{under}$) and overordering ($C_{over}$) costs as follows:

$$s = TINV \quad 2 \cdot \quad 1 - \frac{C_{under}}{C_{under} + C_{over}} \quad \text{, number of forecasted data points} \tag{10.2}$$

where $\frac{C_{under}}{C_{under} + C_{over}}$ is the optimal service level that represents the probability of satisfying all demand for remanufactured products in a particular period, and *TINV* is the EXCEL function returning the inverse of the student t-distribution. Assuming $C_{under}$= 500 and $C_{over}$ = 2, we can determine the values for the s and SS factor as follows:

$$s = TINV \quad 2 \cdot \quad 1 - \frac{500}{500 + 2} \quad , 24 \quad = 2.894$$

SS factor = $1 + s \cdot StdDev_{A/F} = 1 + 2.894 \cdot 0.081 = 1.235$

According to this SS factor, the firm should have a safety stock for each period that is approximately equal to 24% of the forecasted demand for that period.

Table 10.2 presents the MRP table for the product. In this table, the row "forecasted demand" is taken directly from the remanufactured product's demand forecasts (see Table 10.1). The row "forecast *SS factor" is given by the row "forecasted demand" multiplied by the SS multiplier (1.235). For example, for week 19, the entry in this row is 190 * 1.235 = 235. Therefore, the target beginning inventory for week 19 is 235 units. The row "actual demand" corresponds to actual demand for remanufactured products. So, for example, for week 19, the forecasted demand was 190 units, but the actual demand turned out to be 203 units. "On-hand actual" describes the on-hand inventory of the product at the end of the period, which is equal to 32 units (235 target inventory minus 203 actual demand) in week 19. "Planned on-hand" is the expected inventory at the end of a period. This row is only calculated for future weeks (i.e., week 25 and beyond) by subtracting "forecasted demand" from the target inventory (forecasted demand * SS factor).

It must be noted that the firm has 34 products at the end of week 17 (i.e., beginning of week 18). Given a target inventory of 401 and a starting inventory of 34, the firm has a "net requirement" of 367 (=401–34) in week 18. The row "planned order receipt" is equal to the "net requirement" row. Since the lead time is 1 week, the row "planned order release" means the firm has to release a production order of 367 products at the beginning of week 17 in order to have 367 products at the beginning of week 18.

We can interpret the remanufacturing plan going forward (i.e., at the end of week 24) as follows. The number of products remanufactured in week 25 is based on the demand forecasts for week 26 since the lead time is 1 week. Demand forecast for week 26 is 200; thus, the target inventory (forecasted demand * SS factor) at the beginning of week 26 is 247 (= 200 *1.235). Since the projected inventory at the end of week 25 is 55, the firm has a net

**TABLE 10.2**

Implementation of MRP-based Production Planning Methodology

| **Week** | | **18** | **19** | **20** | **21** | **22** | **23** | **24** | **25** | **26** | **27** | **28** | **29** | **30** | **31** | **32** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Forecasted demand** | | 325 | 190 | 170 | 200 | 220 | 185 | 145 | 235 | 200 | 285 | 265 | 225 | 300 | 195 | 225 |
| **Forecast*SS factor** | | 401 | 235 | 210 | 247 | 272 | 228 | 179 | 290 | 247 | 352 | 327 | 278 | 371 | 241 | 278 |
| **Actual demand** | | 309 | 203 | 157 | 221 | 199 | 173 | 168 | | | | | | | | |
| **Actual on-hand** | 34 | 92 | 32 | 53 | 26 | 73 | 55 | 11 | | | | | | | | |
| **Planned on-hand** | | | | | | | | 34 | 55 | 47 | 67 | 62 | 53 | 71 | 46 | 53 |
| **Net requirement** | | 367 | 143 | 178 | 194 | 246 | 155 | 124 | 256 | 192 | 305 | 260 | 216 | 318 | 170 | 232 |
| **Planned order receipt** | | 367 | 143 | 178 | 194 | 246 | 155 | 124 | 256 | 192 | 305 | 260 | 216 | 318 | 170 | 232 |
| **Planned order release** | | 143 | 178 | 194 | 246 | 155 | 124 | 256 | 192 | 305 | 260 | 216 | 318 | 170 | 232 | 169 |

*Notes:* Lead Time = 1 week; SS factor = 1.235; the (shaded) period indicates the current period.

requirement of 192 (= 247 – 55) for week 26, which is the planned remanufacturing production ("planned order release") for week 25.

## 10.3 Production Planning for Component Remanufacturing

Gupta and Taleb (1994) developed an MRP-based production planning methodology, called reverse MRP, by considering the demand for disassembled components. The aim of this methodology is to determine the number of root items to be disassembled in order to satisfy the demand for the components harvested from root items.

There is one interesting difference between reverse MRP and traditional MRP. In traditional MRP, the demand comes from a single source since only the end item (root) is demanded. The main objective is to determine a schedule for subassemblies that are used in the assembly of the end item. However, in reverse MRP, demand comes from multiple sources since the components or leaf items disassembled from a root are demanded. In addition, there is interdependence among these leaf items since the same root item is disassembled to satisfy their demands.

The following inputs are required by the algorithm:

- Item numbers
- The parent of each item
- The yield associated with each parent item
- Disassembly lead time for each parent item
- Ordering lead time of the root
- The planning horizon
- Gross requirements of leaf items
- Scheduled receipts from external resources
- Beginning inventories

All items are numbered starting from the root item (i.e., Root Item No. 1). The algorithm starts with the largest item number (i.e., the component at the lowest level). For this item and all its brothers, "On hand before disassembly" and "Net Requirement" are calculated as follows:

```
If
[(On hand after disassembly)$_{t-1}$ + (Scheduled receipts from external resources)$_t$] – (Gross Requirements)$_t$ >0
       Then
       {(Net Requirement)$_t$ = 0
       (On hand before disassembly) = [(On hand after disassembly)$_{t-1}$ + (Scheduled receipts from external resources)$_t$]- (Gross Requirements)$_t$ }
```

```
Else
      {(Net Requirement)_t = (Gross Requirements)_t - [(On hand
after disassembly)_{t-1} + (Scheduled       receipts from
external resources)_t]
      (On hand before disassembly) = 0}
```

For the parent item in the module (the item investigated, its brothers, and the parent item are considered as a module), the "gross requirements disassembled" are determined as follows:

- Divide net requirement of each sibling by its yield from the parent.
- Take the maximum of these ratios as "gross requirements disassembled" for the parent item for period *t*.

The foregoing calculations are repeated for all periods in the planning horizon. After that, "gross requirements disassembled" for the parent item are offset by the disassembly lead time of the parent item to obtain the "disassembly schedule" of the parent item.

The parent item can also be regarded as a sibling in a module that is at a lower level in the product structure. Then, the "disassembly schedule" of the parent item determined before becomes its "gross requirements."

The foregoing calculations are done for all modules. Finally, "on hand," "net requirements," and "time-phased planned order release" are determined for the root item using traditional MRP logic.

### 10.3.1 Numerical Example

In order to illustrate the logic of reverse MRP, we provide a numerical example. The assembly structure for the product considered in the example is given in Figure 10.1. For the same product, the disassembly product structure can be seen in Figure 10.2. The product involves six modules that were indicated in Figure 10.2 with dotted areas. Table 10.3 provides demand, on-hand inventory, and lead-time information for all components, while scheduled receipts from external sources for all components are provided in Table 10.4.

Reverse MRP tables for all modules are presented in Figures 10.3 through 10.8. Here, we provide detailed explanations for the MRP tables associated with Module 1 (Figure 10.3). The values in the tables associated with the other modules can be interpreted in a similar way.

Module 1 involves one parent item (K) and two siblings (N and O).

#### *PERIOD 1*

We start with sibling O, which has 20 units "gross requirements" in the first period. "On hand after disassembly (beginning inventory)" is 45 units, and "scheduled receipts from external sources" are 5 units. So, "on hand before disassembly" is 45 + 5 = 50 units. Since this value is greater than gross requirements, "net requirement" for the first period is 0.

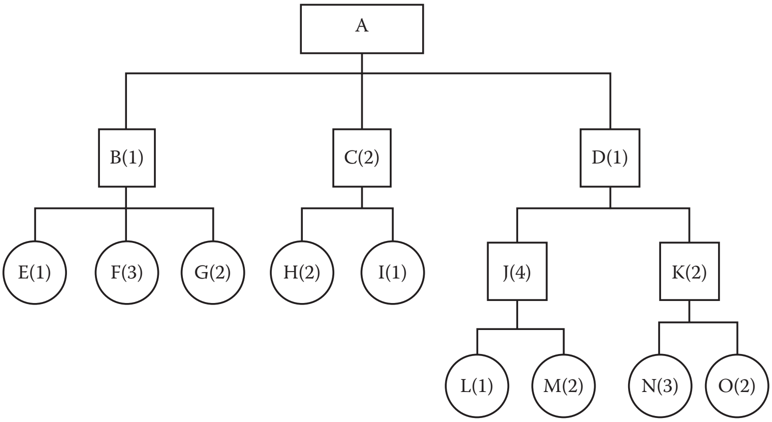

**FIGURE 10.1**
Product structure for assembly.

Sibling N has 15 units "gross requirements" in the first period. "On hand after disassembly (beginning inventory)" is 50 units, and "scheduled receipts from external sources" are 6 units. So, "on hand before disassembly" is 50 + 6 = 56 units. Since this value is greater than "gross requirements," "net requirement" for the first period is 0.

Since "net requirement" is 0 for both siblings, "Gross requirement disassembled" is 0 for the parent item K in period 1.

*PERIOD 2*

Sibling O has 35 units "gross requirements" in the second period. "On hand after disassembly (beginning inventory)" is 30 units, and there is no

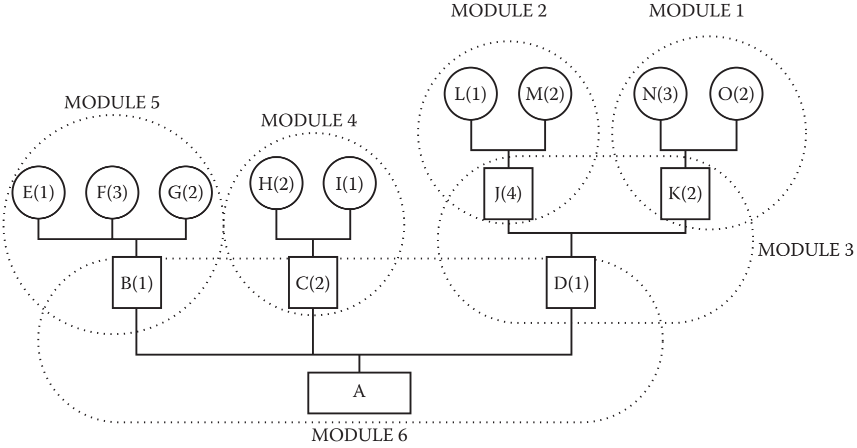

**FIGURE 10.2**

Product structure for disassembly.

**TABLE 10.3**

Demand, On-hand Inventory, and Lead-time Information for Components

| **Item** | **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** | **K** | **L** | **M** | **N** | **O** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Demand in week** | | | | | | | | | | | | | | | |
| **1** | — | — | — | — | 0 | 35 | 0 | 80 | 0 | — | — | 25 | 15 | 123 | 18 |
| **2** | — | — | — | — | 20 | 55 | 25 | 0 | 0 | — | — | 45 | 24 | 243 | 29 |
| **3** | — | — | — | — | 80 | 100 | 0 | 95 | 0 | — | — | 25 | 0 | 0 | 0 |
| **4** | — | — | — | — | 0 | 90 | 100 | 320 | 543 | — | — | 0 | 0 | 0 | 0 |
| **5** | — | — | — | — | 100 | 0 | 100 | 45 | 321 | — | — | 0 | 45 | 0 | 0 |
| **6** | — | — | — | — | 250 | 0 | 50 | 0 | 200 | — | — | 0 | 98 | 120 | 45 |
| **7** | — | — | — | — | 0 | 100 | 0 | 0 | 0 | — | — | 55 | 123 | 32 | 56 |
| **8** | — | — | — | — | 0 | 20 | 0 | 248 | 0 | — | — | 75 | 0 | 0 | 76 |
| **On-hand inventory** | **5** | **10** | **15** | **8** | **20** | **40** | **30** | **70** | **90** | **5** | **12** | **50** | **75** | **50** | **45** |
| **Lead time** | **1** | **2** | **1** | **1** | — | — | — | — | — | **1** | **1** | — | — | — | — |

**TABLE 10.4**

Scheduled Receipts from External Resources for Components

| Item | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Scheduled Receipts from External Sources in Week* | | | | | | | | | | | | | | | |
| **1** | — | 1 | 2 | 0 | 2 | 0 | 0 | 2 | 1 | 2 | 2 | 0 | 10 | 6 | 5 |
| **2** | — | 1 | 1 | 0 | 3 | 1 | 0 | 3 | 1 | 3 | 0 | 0 | 2 | 12 | 0 |
| **3** | — | 1 | 3 | 9 | 2 | 2 | 1 | 4 | 2 | 4 | 9 | 2 | 0 | 0 | 0 |
| **4** | — | 3 | 0 | 0 | 2 | 1 | 3 | 1 | 3 | 0 | 1 | 4 | 0 | 20 | 2 |
| **5** | — | 0 | 0 | 2 | 2 | 0 | 4 | 2 | 1 | 0 | 2 | 14 | 0 | 0 | 10 |
| **6** | — | 0 | 1 | 1 | 6 | 0 | 1 | 0 | 1 | 0 | 5 | 1 | 5 | 21 | 12 |
| **7** | — | 0 | 2 | 0 | 0 | 3 | 2 | 1 | 0 | 5 | 6 | 0 | 6 | 0 | 0 |
| **8** | — | 0 | 3 | 0 | 0 | 3 | 0 | 0 | 0 | 5 | 0 | 0 | 15 | 5 | 7 |

| | | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item O** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 20 | 35 | 0 | 0 | 0 | 45 | 56 | 76 |
| Scheduled receipts from external resources | | 5 | 0 | 0 | 2 | 10 | 12 | 0 | 7 |
| On hand before disassembly | | 50 | 30 | 123 | 125 | 135 | 147 | 154 | 127 |
| Net requirement | | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 128 | 0 | 0 | 0 | 52 | 22 | 0 |
| On hand after disassembly | 45 | 30 | 123 | 123 | 125 | 135 | 154 | 120 | 51 |

| | | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item N** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 15 | 243 | 0 | 0 | 0 | 120 | 32 | 0 |
| Scheduled receipts from external resources | | 6 | 12 | 0 | 20 | 0 | 21 | 0 | 5 |
| On hand before disassembly | | 56 | 53 | 2 | 22 | 22 | 43 | 1 | 7 |
| Net requirement | | 0 | 190 | 0 | 0 | 0 | 77 | 31 | 0 |
| Scheduled receipts from disassembly | | 0 | 192 | 0 | 0 | 0 | 78 | 33 | 0 |
| On hand after disassembly | 50 | 41 | 2 | 2 | 22 | 22 | 1 | 2 | 7 |

| | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Item K** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirement disassembled | 0 | 64 | 0 | 0 | 0 | 26 | 11 | 0 |
| Disassembled schedule | 64 | 0 | 0 | 0 | 26 | 11 | 0 | |

**FIGURE 10.3**

Reverse MRP calculations for Module 1.

"scheduled receipts from external sources." So, "on hand before disassembly" is 30 + 0 = 30 units. Since this value is less than "gross requirements," "net requirement" for the second period is 35–30 = 5 units.

Sibling N has 243 units "gross requirements" in the second period. "On hand after disassembly (beginning inventory)" is 41 units, and "scheduled receipts from external sources" is equal to 12 units. So, "on hand before disassembly" is 41 + 12 = 53 units. Since this value is less than gross requirements, net requirement for the first period is 243 − 53 = 190 units.

The yield of O from the parent item K is 2. So, the "net requirement/yield" ratio is equal to $[5/2] = [2.5] = 3$

The yield of N from the parent item K is 3. So, "net requirement/yield" ratio is equal to $[190/3] = [63.3] = 64$.

"Gross requirement disassembled" for parent item K = max {3, 64} = 64.

The rest of the periods for Module 1 are carried out in a similar fashion (see Figure 10.3). Results for the remaining modules are shown in Figures 10.4 through 10.8.

| | | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item M** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 15 | 24 | 0 | 0 | 45 | 98 | 123 | 0 |
| Scheduled receipts from external resources | | 10 | 2 | 0 | 0 | 0 | 5 | 6 | 15 |
| On hand before disassembly | | 85 | 72 | 58 | 74 | 74 | 34 | 6 | 16 |
| Net requirement | | 0 | 0 | 0 | 0 | 0 | 64 | 117 | 0 |
| Scheduled receipts from disassembly | | 0 | 10 | 16 | 0 | 0 | 64 | 118 | 0 |
| On hand after disassembly | 75 | 70 | 58 | 74 | 74 | 29 | 0 | 1 | 16 |

| | | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item L** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 20 | 45 | 25 | 0 | 0 | 0 | 55 | 75 |
| Scheduled receipts from external resources | | 0 | 0 | 2 | 4 | 14 | 1 | 0 | 0 |
| On hand before disassembly | | 50 | 30 | 2 | 5 | 19 | 20 | 116 | 238 |
| Net requirement | | 0 | 15 | 23 | 0 | 0 | 0 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 10 | 16 | 0 | 0 | 64 | 118 | 0 |
| On hand after disassembly | 75 | 70 | 58 | 74 | 74 | 29 | 0 | 1 | 16 |

| | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Item J** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirement disassembled | 0 | 5 | 8 | 0 | 0 | 32 | 59 | 0 |
| Disassembled schedule | 5 | 8 | 0 | 0 | 32 | 59 | 0 | |

**FIGURE 10.4**
Reverse MRP calculations for Module 2.

| | | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item K** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 59 | 0 | 0 | 0 | 26 | 11 | 0 | 0 |
| Scheduled receipts from external resources | | 2 | 0 | 9 | 1 | 2 | 5 | 6 | 0 |
| On hand before disassembly | | 62 | 3 | 12 | 13 | 15 | 6 | 31 | 31 |
| Net requirement | | 0 | 0 | 0 | 0 | 11 | 5 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 0 | 0 | 0 | 12 | 30 | 0 | 0 |
| On hand after disassembly | 60 | 3 | 3 | 12 | 13 | 1 | 25 | 31 | 31 |

| | | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item J** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 6 | 0 | 0 | 32 | 58 | 0 | 0 |
| Scheduled receipts from external resources | | 2 | 3 | 4 | 0 | 0 | 0 | 5 | 5 |
| On hand before disassembly | | 7 | 10 | 8 | 8 | 8 | 0 | 7 | 12 |
| Net requirement | | 0 | 0 | 0 | 0 | 24 | 58 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 0 | 0 | 0 | 24 | 60 | 0 | 0 |
| On hand after disassembly | 5 | 7 | 4 | 8 | 8 | 0 | 2 | 7 | 12 |

| | **Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Item D** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirement disassembled | 0 | 0 | 0 | 0 | 6 | 15 | 0 | 0 |
| Disassembled schedule | 0 | 0 | 0 | 6 | 15 | 0 | 0 | 0 |

**FIGURE 10.5**
Reverse MRP calculations for Module 3.

## 10.4 Production Planning Considering Both Manufacturing and Remanufacturing

In this section we consider the case where both newly produced and remanufactured parts/products are used to meet the demand. In this type of hybrid system, the production control methodology must provide the required coordination between manufacturing and remanufacturing. Inderfurth and Teunter (2003) developed an MRP-based production control methodology for hybrid manufacturing/remanufacturing systems. In this subsection, we explain this methodology with a numerical example. The product structure considered in the example can be seen in Figure 10.9.

| | | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item I** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 0 | 0 | 543 | 321 | 200 | 0 | 0 |
| Scheduled receipts from external resources | | 1 | 1 | 2 | 3 | 1 | 1 | 0 | 0 |
| On hand before disassembly | | 91 | 92 | 94 | 105 | 1 | 1 | 0 | 0 |
| Net requirement | | 0 | 0 | 0 | 438 | 320 | 199 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 0 | 8 | 438 | 320 | 199 | 0 | 0 |
| On hand after disassembly | 90 | 91 | 92 | 102 | 0 | 0 | 0 | 0 | 0 |

| | | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item H** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 0 | 95 | 320 | 45 | 0 | 0 | 248 |
| Scheduled receipts from external resources | | 2 | 3 | 4 | 1 | 2 | 0 | 1 | 0 |
| On hand before disassembly | | 72 | 75 | 79 | 1 | 559 | 1154 | 1553 | 1553 |
| Net requirement | | 0 | 0 | 16 | 319 | 0 | 0 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 0 | 16 | 876 | 640 | 398 | 0 | 0 |
| On hand after disassembly | 70 | 72 | 75 | 0 | 557 | 1154 | 1552 | 1553 | 1305 |

| | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Item C** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirement disassembled | 0 | 0 | 8 | 438 | 320 | 199 | 0 | 0 |
| Disassembled schedule | 0 | 8 | 438 | 320 | 199 | 0 | 0 | 0 |

**FIGURE 10.6**
Reverse MRP calculations for Module 4.

We particularly consider subassembly C. This subassembly can be obtained in two ways:

- It can be manufactured using components E, F, and G. The lead time for this operation is 1 week.
- It can be obtained through the disassembly of core A (remanufacturing). The lead time for this operation is 2 weeks.

In order to show the impact of remanufacturing on MRP calculations, we first present the standard MRP calculations without considering remanufacturing (see Table 10.5). The input data is shown in bold.

When the remanufacturing option is considered with manufacturing, the following issues must be resolved:

- The priority between manufacturing and remanufacturing must be determined. For instance, if remanufacturing is less costly, then the

| | | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item G** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 0 | 0 | 100 | 100 | 50 | 0 | 0 |
| Scheduled receipts from external resources | | 0 | 0 | 1 | 3 | 4 | 1 | 2 | 0 |
| On hand before disassembly | | 30 | 30 | 31 | 34 | 4 | 1 | 417 | 417 |
| Net requirement | | 0 | 0 | 0 | 66 | 96 | 49 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 0 | 0 | 66 | 96 | 464 | 0 | 0 |
| On hand after disassembly | 30 | 30 | 30 | 31 | 0 | 0 | 415 | 417 | 417 |

| | | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item F** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 0 | 0 | 90 | 0 | 0 | 100 | 20 |
| Scheduled receipts from external resources | | 0 | 1 | 2 | 1 | 0 | 0 | 3 | 3 |
| On hand before disassembly | | 40 | 41 | 43 | 44 | 53 | 197 | 896 | 799 |
| Net requirement | | 0 | 0 | 0 | 46 | 0 | 0 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 0 | 0 | 99 | 144 | 696 | 0 | 0 |
| On hand after disassembly | 40 | 40 | 41 | 43 | 53 | 197 | 893 | 796 | 779 |

| | | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item E** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 0 | 0 | 0 | 100 | 250 | 0 | 0 |
| Scheduled receipts from external resources | | 2 | 3 | 2 | 2 | 2 | 6 | 0 | 0 |
| On hand before disassembly | | 22 | 25 | 27 | 29 | 64 | 18 | 0 | 0 |
| Net requirement | | 0 | 0 | 0 | 0 | 36 | 232 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 0 | 0 | 33 | 48 | 232 | 0 | 0 |
| On hand after disassembly | 20 | 22 | 25 | 27 | 62 | 12 | 0 | 0 | 0 |

| | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Item B** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirement disassembled | 0 | 0 | 0 | 33 | 48 | 232 | 0 | 0 |
| Disassembled schedule | 0 | 33 | 48 | 232 | 0 | 0 | 0 | 0 |

**FIGURE 10.7**
Reverse MRP calculations for Module 5.

net requirements can be satisfied through remanufacturing as long as there are remanufacturables. New part manufacturing is only done when there are not enough remanufacturables.

- An appropriate disposal policy must be set for remanufacturables. This policy may be based on a threshold level. If the number of remanufacturables exceeds this threshold, it is reduced to the threshold by disposal.

| | | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item D** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 0 | 0 | 7 | 3 | 0 | 0 | 0 |
| Scheduled receipts from external resources | | 0 | 0 | 9 | 0 | 2 | 1 | 0 | 0 |
| On hand before disassembly | | 8 | 8 | 38 | 230 | 385 | 482 | 482 | 482 |
| Net requirement | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 21 | 192 | 160 | 99 | 0 | 0 | 0 |
| On hand after disassembly | 8 | 8 | 29 | 230 | 383 | 481 | 482 | 482 | 482 |

| | | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item C** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 8 | 438 | 320 | 199 | 0 | 0 | 0 |
| Scheduled receipts from external resources | | 2 | 1 | 3 | 0 | 0 | 1 | 2 | 3 |
| On hand before disassembly | | 17 | 18 | 55 | 1 | 1 | 1 | 3 | 6 |
| Net requirement | | 0 | 0 | 383 | 319 | 198 | 0 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 42 | 384 | 320 | 198 | 0 | 0 | 0 |
| On hand after disassembly | 15 | 17 | 52 | 1 | 1 | 0 | 1 | 3 | 6 |

| | | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Item B** | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| Gross requirements | | 0 | 33 | 48 | 232 | 0 | 0 | 0 | 0 |
| Scheduled receipts from external resources | | 1 | 1 | 1 | 3 | 0 | 0 | 0 | 0 |
| On hand before disassembly | | 11 | 12 | 1 | 148 | 76 | 175 | 175 | 175 |
| Net requirement | | 0 | 21 | 47 | 84 | 0 | 0 | 0 | 0 |
| Scheduled receipts from disassembly | | 0 | 21 | 192 | 160 | 99 | 0 | 0 | 0 |
| On hand after disassembly | 10 | 11 | 0 | 145 | 76 | 175 | 175 | 175 | 175 |

| | Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Item A** | **1** | **2** | 3 | **4** | **5** | **6** | **7** | **8** |
| Gross requirement disassembled | 0 | 21 | 192 | 160 | 99 | 0 | 0 | 0 |
| Disassembled schedule | 21 | 192 | 160 | 99 | 0 | 0 | 0 | 0 |

**FIGURE 10.8**
Reverse MRP calculations for Module 6.

In our example, priority is given to remanufacturing, and whenever the amount of remanufacturables exceeds 20 units, disposal takes place.

MRP calculations for subassembly C with both manufacturing and remanufacturing can be seen in Table 10.6. The input data is shown in bold.

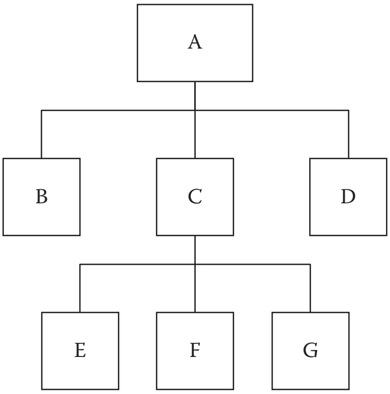

**FIGURE 10.9**
Product structure considered in the example.

**TABLE 10.5**
MRP Calculations for Subassembly C Considering Only Manufacturing

| | | **Period** | | | | |
|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** |
| Gross requirements | | **40** | **50** | **25** | **30** | **10** |
| Scheduled receipts | | **10** | | | | |
| Projected on hand | **30** | 0 | 0 | 0 | 0 | 0 |
| Net requirements | | 0 | 50 | 25 | 30 | 10 |
| Planned order receipts | | | 50 | 25 | 30 | 10 |
| Planned order releases | | 50 | 25 | 30 | 10 | |

**TABLE 10.6**
MRP Calculations for Subassembly C Considering Both Manufacturing and Remanufacturing

| | | **Period** | | | | |
|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** |
| Gross requirements | | **40** | **50** | **25** | **30** | **10** |
| Scheduled receipts manufacturing | | **10** | — | — | — | — |
| Scheduled receipts remanufacturing | | **5** | **10** | — | — | — |
| Projected serviceables on hand | **30** | 5 | 0 | 0 | 0 | 0 |
| Net requirements | | 0 | 35 | 25 | 30 | 10 |
| Expected returns remanufacturables | | **30** | **20** | **10** | **20** | **20** |
| Projected remanufacturables on hand | **20** | 20 | 10 | 10 | 20 | 20 |
| Planned order receipts remanufacturing | | — | — | 25 | 30 | 10 |
| Planned order receipts manufacturing | | — | 35 | — | — | — |
| Planned order release disposal | | 5 | 0 | 0 | 10 | 20 |
| Planned order release remanufacturing | | 25 | 30 | 10 | 0 | — |
| Planned order release manufacturing | | 35 | 0 | 0 | 0 | — |

## 10.5 Other Models

Development of production planning models for remanufacturing systems is an active research area. In Ferrer and Whybark (2001), an MRP-based methodology is developed in order to solve the following planning issues: how many and which cores to buy, what mix of cores to disassemble, and which components should be assembled to meet demand. Souza and Ketzenberg (2002) and Souza et al. (2002) use a two-stage GI/G/1 queuing network model to find the optimal, long-run production mix that maximizes profit subject to the service-level constraint for a firm that meets demand for an order with remanufactured products, new products, or a mix of both. They also consider a capacity limitation on production and a service-level constraint measured in terms of the average order lead time. The robustness of the model is also tested by presenting a DES-based analysis of some real-life issues such as stochastic product returns and stochastic production yield. Gupta and Veerakamolmal (2001) determine the number of products to disassemble in order to fulfill the demand for various components for remanufacturing in different time periods using an integer programming (IP)–based algorithm. The mathematical programming model proposed by Jayaraman (2006) determines the number of units of core type with a nominal quality level that is disassembled, disposed, remanufactured, and acquired in a given time period, as well as the inventory of modules and cores that remain at the end of a given time period. Kim et al. (2006) determine the quantity of products/parts processed in the remanufacturing facilities/subcontractors and the amount of parts purchased from the external suppliers by developing an MIP model based on the maximization of the total remanufacturing cost saving. The short-term bulk recycling planning proposed by Lu et al. (2006) can determine what products to accept, process, and reprocess. The expected number of remanufactured units to be completed in each future period together with the number of components needed to be purchased to avoid any projected shortages are determined by DePuy et al. (2007) using a production planning method. Li et al. (2006) develop a heuristic approach to uncapacitated production planning with multiple product types, returned product remanufacturing, and demand substitution. A genetic-algorithms-based approach is proposed by Li et al., (2007) for a multiperiod production planning problem with return products under substitution and capacity constraints. In Li et al. (2009), production planning and control policies for dedicated remanufacturing are optimized by combining a hybrid-cell-evaluated GA with a DES model. The MILP-based aggregate production planning model proposed by Xanthopoulos and Iakovou (2009) determines how many EOL products and components should be collected, nondestructively or destructively disassembled, recycled, remanufactured, stored, backordered, and disposed in each period. Denizel et al. (2010) consider the uncertain quality of product returns while developing a multiperiod remanufacturing planning model.

## 10.6 Conclusions

In this chapter, three models were presented to address production planning issues in remanufacturing. In the first model, a production schedule is developed for the remanufacture of a product. The second model involved the development of an MRP-based production schedule considering the demand for disassembled components. In the third model, an MRP-based schedule was developed considering the use of both newly produced and remanufactured parts/products to meet demand. The previous section presented an overview of production planning models developed for remanufacturing systems.

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# 11

# *Capacity Planning*

## 11.1 The Issue

Capacity planning in remanufacturing involves the determination of capacity requirements considering the changing demands for remanufactured components or products. Traditional capacity planning techniques cannot directly be applied to remanufacturing. The main reason for this is the uncertain processing operational requirements of components or products in remanufacturing. Due to the high level of uncertainty associated with the condition of product returns, all the parts in one product may be remanufacturable, while there may not be any remanufacturable part in another product.

In this chapter we explain a rough-cut capacity planning (RCCP) approach that considers the uncertainty associated with processing operations.

## 11.2 A Rough-Cut Capacity Planning Approach to Remanufacturing

Guide and Spencer (1997) proposed a rough-cut capacity planning technique by considering two major sources of uncertainty in the capacity planning of remanufacturing systems:

- Stochastic routing files
- Stochastic material replacement factors

In the following subsections, we present the details of this technique by presenting relevant formulas and a numerical example.

### 11.2.1 Stochastic Routing Files

In manufacturing, while assembling a specific type of product, all stations in its routing file must be visited in order to have a complete product. However, in remanufacturing, a particular product type visits only those stations that are associated with the parts requiring repair or remanufacturing. In order to account for this difference, the following occurrence factor (*OFC*) is employed:

$$OFC_{ij} = \frac{\sum_{p=1}^{NP_j} RT_{ijp}}{NP_j} \tag{11.1}$$

where

$OFC_{ij}$ : occurence factor of part type $j$ at workstation $i$

$RT_{ijp}$ : 1 if workstation $i$ is visited by part type $j$, 0 otherwise $(p = 1,2,\ldots, NP_j)$

$NP_j$ : Total number of part type $j$ sent for processing

It must be noted that ignorance of OFC will result in the overestimation of capacity required in a station.

### 11.2.2 Stochastic Material Replacement Factors

In remanufacturing, a disassembled component may not be repairable. In this case, an irreparable component is replaced with a brand new component. In other words, stations do not spend time on irreparable components. That is why the following material recoverability rate factor (*MRF*) was developed:

$$MRF_j = 1 - \frac{\sum_{t=1}^{T} SC_{tj}}{TI_j} \tag{11.2}$$

where

$MRF_j$ : material recovery rate for part $j$

$SC_{tj}$ : number of units type $j$ scrapped during period $t$ $(t = 1,2,3,\ldots,T)$

$TI_{tj}$ : total number of units type $j$ introduced

### 11.2.3 Calculating Station Capacity Requirements

Considering stochastic routing files and stochastic material replacement factors, the following formula is used to determine the capacity required at a station:

$$CAP_{it} = \sum_{j=1}^{R} [(AMPS_{jt} \cdot PT_{ij}) \cdot OFC_{ij}] \tag{11.3}$$

where

$CAP_{it}$ : Required capacity of station $i$ during period $t$ $(i = 1, 2, \ldots, w$ and $t=1,2,\ldots,T)$

$AMPS_{jt}$ : Adjusted master production scheduled quantity for part $j$ $(j = 1, 2, \ldots, R)$ in time period $t$.

$PT_{ij}$ : Time required to produce one unit of part $j$ in station $i$

$OFC_{ij}$ : Occurence factor for part $j$ in station $i$

It must be noted that $AMPS_{jt}$ is calculated by multiplying the master production scheduled (*MPS*) quantity in period $t$ by the *MRF* for the part under consideration.

### 11.2.4 Numerical Example

The bill of material of the product considered in this example is given in Figure 11.1. In this figure, the number in parentheses represents the quantity of a component required to produce one unit of the parent item. *MPS* for the product can be seen in Table 11.1. In this example, we develop the capacity plan for three stations responsible for the repair/remanufacture of six components, namely, D, E, F, G, H, and I. Table 11.2 provides station, processing time, setup time, lot size, and OFC information for each component.

First, the adjusted MPS (*AMPS*) quantities are determined for each component (see Table 11.3). As an example, the *AMPS* quantity for part D in week 1 can be calculated as follows:

$$AMPS_{D,1} = \overset{\substack{\text{MPS for product} \\ \text{A in week 1}}}{350} \cdot \overset{\substack{\text{Multiplicity of} \\ \text{component D}}}{2} \cdot \overset{\substack{\text{MRF for} \\ \text{component D}}}{0.80} = 560$$

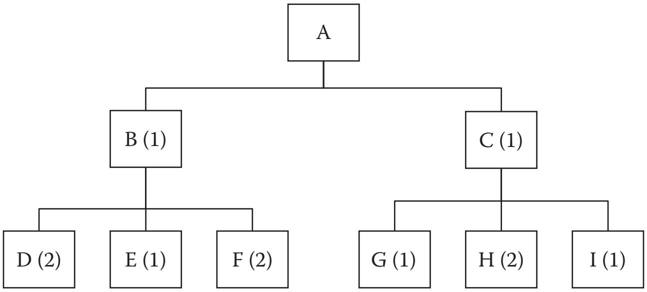

**FIGURE 11.1**
Product structure.

**TABLE 11.1**

Master Production Schedule for Product A

| Week | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| MPS | 300 | 245 | 240 | 255 | 200 | 180 | 270 | 220 | 220 | 240 |

**TABLE 11.2**

Various Characteristics of Investigated Components

| Station | Part | Processing time/item (minutes) | Setup time/ lot (minutes) | Lot size | OFC |
|---|---|---|---|---|---|
| 1 | D | 2 | 1 | 20 | 0.80 |
| 1 | E | 6 | 1 | 10 | 0.75 |
| 2 | F | 3 | 1 | 15 | 0.60 |
| 2 | G | 4 | 2 | 15 | 0.90 |
| 3 | H | 1.5 | 1 | 25 | 0.90 |
| 3 | I | 6.5 | 1.5 | 25 | 0.85 |

**TABLE 11.3**

Adjusted MPS Quantities

| | | Adjusted MPS Quantity | | | | | |
|---|---|---|---|---|---|---|---|
| **Week** | **MPS Quantity** | **D** | **E** | **F** | **G** | **H** | **I** |
| 1 | 350.00 | 560.00 | 262.50 | 420.00 | 315.00 | 630.00 | 297.50 |
| 2 | 300.00 | 480.00 | 225.00 | 540.00 | 270.00 | 540.00 | 255.00 |
| 3 | 290.00 | 464.00 | 217.50 | 522.00 | 261.00 | 522.00 | 246.50 |
| 4 | 330.00 | 528.00 | 247.50 | 594.00 | 297.00 | 594.00 | 280.50 |
| 5 | 370.00 | 592.00 | 277.50 | 666.00 | 333.00 | 666.00 | 314.50 |
| 6 | 255.00 | 408.00 | 191.25 | 459.00 | 229.50 | 459.00 | 216.75 |
| 7 | 345.00 | 552.00 | 258.75 | 621.00 | 310.50 | 621.00 | 293.25 |
| 8 | 400.00 | 640.00 | 300.00 | 720.00 | 360.00 | 720.00 | 340.00 |
| 9 | 310.00 | 496.00 | 232.50 | 558.00 | 279.00 | 558.00 | 263.50 |
| 10 | 295.00 | 472.00 | 221.25 | 531.00 | 265.50 | 531.00 | 250.75 |

**TABLE 11.4**

Unit Processing Times (minutes)

| Component | Station 1 | Station 2 | Station 3 |
|---|---|---|---|
| D | 2.05 | — | — |
| E | 6.10 | — | — |
| F | — | 3.07 | — |
| G | — | 4.13 | — |
| H | — | — | 1.54 |
| I | — | — | 6.56 |

Then the *PT* value is calculated for each component (see Table 11.4). For instance, the calculation of the *PT* value for component G can be presented as

$$PT_{2,G} = \overset{\text{Unit processing time for G}}{4} + \frac{\overset{\text{Setup time per lot for G}}{2}}{\underset{\text{Lot size for G}}{15}} = 4.13 \text{ minutes}$$

Using *AMPS* and *PT* values, the capacity requirement for each station is determined (see Table 11.5). This can be exemplified for station 3 in week 2 as follows:

$$CAP_{32} = (540 \cdot 1.54) \cdot 0.90 + (255 \cdot 6.56) \cdot 0.85 = 2170.32 \text{ minutes}$$

**TABLE 11.5**

Capacity Requirements of Stations Per Time Period (Minutes)

| Week | Station 1 | Station 2 | Station 3 |
|---|---|---|---|
| 1 | 2119.34 | 1944.60 | 2532.04 |
| 2 | 1816.58 | 1998.00 | 2170.32 |
| 3 | 1756.02 | 1931.40 | 2097.98 |
| 4 | 1998.23 | 2197.80 | 2387.35 |
| 5 | 2240.44 | 2464.20 | 2676.73 |
| 6 | 1544.09 | 1698.30 | 1844.77 |
| 7 | 2089.06 | 2297.70 | 2495.87 |
| 8 | 2422.10 | 2664.00 | 2893.76 |
| 9 | 1877.13 | 2064.60 | 2242.66 |
| 10 | 1786.30 | 1964.70 | 2134.15 |

**TABLE 11.6**

Available Capacity at each Station

| Station | Available Time (minutes) | Utilization | Efficiency | Capacity |
|---|---|---|---|---|
| 1 | 2400 | 0.97 | 0.99 | 2304.72 |
| 2 | 2400 | 0.96 | 0.99 | 2280.96 |
| 3 | 2400 | 0.98 | 0.98 | 2304.96 |

Available capacity at a station (*AV_CAP)* for each week is calculated using the following equation:

$$AV\_CAP = H*W*U*E \tag{11.4}$$

where

*H:* Number of hours available per week
*W:* Number of employees at the station
*U:* Utilization
*E*: Efficiency

Assuming a 5-day work week with one 8-hour shift per day and one employee per station, the available capacity at each station can be determined as given in Table 11.6.

We can determine the capacity shortfall of each station by comparing the capacity requirements with the available capacities. This comparison reveals that Station 1 has insufficient capacity in week 8, Station 2 has insufficient capacities in weeks 5, 7, and 8, and Station 3 has insufficient capacities in weeks 1, 4, 5, 7, and 8. Depending on the various factors limiting the company (e.g., financial constraints, labor agreements on the use of overtime, etc.), one or more of the following options can be implemented to deal with the capacity shortfall:

- Adding extra workforce to stations
- Adding extra shifts (second and third shifts)
- Adding extra workdays (Saturday and Sunday shifts)
- Modifying the MPS in a way that demand is shifted to the periods with underutilized capacity

## 11.3 Other Models

Several capacity planning and RCCP techniques were developed by researchers considering the unique characteristics of remanufacturing systems. Guide and Spencer (1997) consider probabilistic material replacement and probabilistic routing files while developing an RCCP method for remanufacturing firms. After comparing the modified RCCP techniques with traditional RCCP techniques, Guide et al. (1997) conclude that traditional RCCP techniques tend to perform poorly in a recoverable environment.

In some studies, remanufacturing capacity plans are developed using LP and/or simulation. Kim et al. (2005) determine the capacity of remanufacturing facilities by developing a mathematical model based on the maximization of the saving from the investment on remanufacturing facilities. System dynamics simulation (SDS) modeling is used by Georgiadis et al. (2006) and Vlachos et al. (2007) in order to develop remanufacturing capacity plans in closed-loop supply chains. Georgiadis et al.'s (2006) SDS model is extended by Georgiadis and Athanasiou (2010) in two ways. First, they consider two sequential product life cycles of two product types. Second, they make a scenario analysis by considering two scenarios about the market with regard to customer preferences over the product types. Franke et al. (2006) develop capacity plans for a cell phone remanufacturing facility by integrating LP and DES.

## 11.4 Conclusions

In this chapter, the capacity planning issue in remanufacturing was discussed by presenting a technique that can generate an RCCP for remanufacturing considering stochastic operation times. A review of the other capacity planning models developed for remanufacturing systems was also presented in the previous section.

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# 12

# Pricing

## 12.1 The Issue

The profitability of a remanufacturing company largely depends on the continuous supply of cores that are obtained by providing incentives to consumers or to collection centers. The value of this incentive (price of the core) is an important tool to ensure a continuous supply of cores. In addition, by changing its value, a remanufacturer can control the number of cores returned. Another important pricing decision is the pricing of remanufactured components. Besides profit, the level of component inventories and the number of disposed components are determined by the pricing decision.

In this chapter we investigate pricing issues in the remanufacturing environment by providing representative models from the literature. First, a model developed for the pricing of cores is presented. Then, another model on pricing of remanufactured components is discussed. We then present an overview of other pricing models in remanufacturing.

## 12.2 Pricing Cores

Liang et al. (2009) developed a mathematical model for pricing cores by assuming that fluctuation of the sale price of core products can be explained using the concept of geometric Brownian motion (GBM). We can summarize the assumptions of this model as follows:

- Perfect information on the condition of cores can be obtained by outlining the quality parameters to the suppliers and inspecting the cores.

- The time interval from cores to core products is between [0, *T*].
- All acquired cores are suitable for remanufacturing.
- A total remanufacturing cost expression is used to represent the sum of all the individual costs associated with remanufacturing, such as dismantling, inspection, quality assurance, logistics and overheads, and cores' transaction costs.
- Any money spent for investments associated with core acquisition and remanufacturing can be paid off only following the sales of core products.
- Interest rate is constant over the period [0, *T*].

Based on the foregoing assumptions, the price of a core is estimated using the following expression:

$$w(x(t),t) = P \cdot e^{-it} + x(t) \cdot \phi(g(x(t),t)) - P \cdot e^{-it} \cdot \phi(h(x(t),t)) - x(t) \qquad (12.1)$$

where

$$g(x(t),t) = \frac{\ln(x(t)/P \cdot e^{-it})}{\sigma \cdot \sqrt{t}} + \frac{1}{2} \cdot \sigma \cdot \sqrt{t} \qquad (12.2)$$

$$h(x(t),t) = \frac{\ln(x(t)/P \cdot e^{-it})}{\sigma \cdot \sqrt{t}} - \frac{1}{2} \cdot \sigma \cdot \sqrt{t} \qquad (12.3)$$

$$\phi(x(t)) = \frac{1}{\sqrt{2 \cdot \pi}} \cdot \int_{-\infty}^{x(t)} e^{-y^2/2}\, dy, \quad x(t) \in R \qquad (12.4)$$

is the standard normal distribution function.
where

$w(x(t), t)$: Core price
$x(t)$: Sale price of core product at time $t$
$\mu$: Drift in resale price
$\sigma$: Volatility of resale price
$i$: Short-term interest rate (assumed to be fixed within time interval [0,*T*])
$P$: Forecasted sale price of core product

### 12.2.1 Numerical Example

Let $x(0) = \$50$, $\quad = 0.30$, $\sigma = 0.30$, $T = 80$ days, and $i = 8\%$. $P$ is taken as \$70. Using these data and Equation (12.1), the core price is calculated as follows:

$$w(x(0),0) = P \cdot e^{-i \cdot t} + x(0) \cdot \phi \; \frac{\ln(x(0)/P \cdot e^{-i \cdot t})}{\sigma \cdot \sqrt{T}} + \frac{1}{2} \cdot \sigma \cdot \sqrt{T}$$

$$- P \cdot e^{-i \cdot t} \cdot \phi \; \frac{\ln(x(0)/P \cdot e^{-i \cdot t}}{\sigma \cdot \sqrt{T}} - \frac{1}{2} \cdot \sigma \cdot \sqrt{T} \; - x(0)$$

$$w(50,0) = 70 \cdot e^{-0.08 \cdot 0} + 50 \cdot \phi \; \frac{\ln(50/70 \cdot e^{-0.08 \cdot 0})}{0.3 \cdot \sqrt{80}} + \frac{1}{2} \cdot 0.3 \cdot \sqrt{80}$$

$$- 70 \cdot e^{-0.08 \cdot 0} \cdot \phi \; \frac{\ln(50/70 \cdot e^{-0.08 \cdot 0})}{0.3 \cdot \sqrt{80}} - \frac{1}{2} \cdot 0.3 \cdot \sqrt{80} \; - 50$$

$$w(50,0) = \$19.99$$

## 12.3 Pricing Components

Vadde et al. (2005) developed models for the pricing of components harvested from end-of-life (EOL) products based on the following assumptions:

- There is no competition from other product recovery companies.
- EOL product acquisition cost is negligible.
- Price reservations and strategic customer behavior do not exist.
- The demand is deterministic.
- One type of discrete product/component is sold.
- There is no inventory replenishment during the selling horizon.
- The demand is described by a continuous, differentiable, and strictly decreasing function.

The following four cases are considered for the product recovery company at the end of the selling horizon:

**Case 1**: There is no need for disposal. In other words, the company is able to sell all $N$ components throughout the selling horizon.

**Case 2**: The fraction of inventory that has to be disposed of does not exceed the prespecified limit $L$.

**Case 3**: The fraction of inventory that has to be disposed of exceeds the prespecified limit $L$, and there is a disposal charge for the surplus.

**Case 4**: Inventory stockouts occur. Contrary to traditional manufacturing systems, in product recovery systems, stockouts do not necessarily negatively affect the future buying behavior of the customer. They may even help in the reduction of holding and disposal costs.

The foregoing four cases are analyzed by considering two main categories: price-dependant demand, and time and price dependent demand.

### 12.3.1 Price-Dependent Demand

First, pricing models are developed for the foregoing four cases by assuming that demand is dependent only on the price of the component.

For Case 1:

The solution of the following equation gives the optimal price:

$$\phi(p^*)\cdot T = N \tag{12.5}$$

where $p^*$ is the optimal price, $T$ is the length of the selling horizon, $N$ is the number of items to be sold by the company by the end of the selling horizon, and $\phi(p)$ is the demand intensity function that gives the number of items in demand per unit time for price $p$.

For Case 2:

The following optimization problem is solved to obtain the optimal price:

$$\max_p p\cdot\phi(p)\cdot T \tag{12.6}$$

$$\beta\cdot[N-\phi(p)\cdot T]\le L \tag{12.7}$$

where $\beta$ is the portion of unsold inventory sent for disposal, and $L$ is the predetermined upper limit on the items that can be disposed of.

For Case 3:

The following optimization problem is solved to obtain the optimal price:

$$\max_p p\cdot\phi(p)\cdot T \tag{12.8}$$

$$\beta\cdot[N-\phi(p)\cdot T]> L \tag{12.9}$$

For Case 4:

Either of the optimal prices determined for the first three cases can be used for this case.

#### *12.3.1.1 Example*

We consider the following demand function:

$$\phi(p) = \frac{1}{e^{2p} - 2} \tag{12.10}$$

With this demand function, the optimal price can be obtained for Cases 1 through 3 as follows:

Case 1:

$$\frac{1}{e^{2p} - 2} \cdot T = N$$

$$p^{*} = \frac{\ln \quad \frac{T}{N} + 2}{2} \tag{12.11}$$

Case 2:

$$\max_{p} \frac{p \cdot T}{e^{2p} - 2} \tag{12.12}$$

$$\beta \cdot \quad N - \frac{T}{e^{2p} - 2} \quad \leq L \tag{12.13}$$

Let $f(p) = \frac{p \cdot T}{e^{2p} - 2}$ and $g(p) = \beta \cdot \quad N - \frac{T}{e^{2p} - 2} \quad - L$

Partial derivatives of these two functions with respect to $p$ can be given as follows:

$$\frac{\partial f}{\partial p} = \frac{T \cdot e^{2p} \cdot (1 - 2 \cdot p) - 2 \cdot T}{(e^{2p} - 2)^2} \tag{12.14}$$

$$\frac{\partial g}{\partial p} = \frac{2 \cdot \beta \cdot T \cdot e^{2p}}{(e^{2p} - 2)^2} \tag{12.15}$$

The Kuhn–Tucker (KKT) conditions can be written as follows:

$$1.\quad \frac{\partial f}{\partial p} - \lambda \cdot \frac{\partial g}{\partial p} \leq 0 \tag{12.16}$$

$$2.\quad p \cdot \quad \frac{\partial f}{\partial p} - \lambda \cdot \frac{\partial g}{\partial p} \quad = 0 \tag{12.17}$$

$$3.\quad N - \frac{T}{e^{2p} - 2} - L \;\leq 0 \tag{12.18}$$

$$4.\quad \lambda \cdot \quad N - \frac{T}{e^{2p} - 2} - L \quad = 0 \tag{12.19}$$

$$5.\quad p \geq 0 \tag{12.20}$$

$$6.\quad \lambda \geq 0 \tag{12.21}$$

where $L \;= \frac{L}{\beta}$, and λ is the Lagrange multiplier. Solving for $p$ using the KKT conditions, one gets

$$p^* = \frac{\ln \quad \frac{T}{N - L} + 2}{2} \tag{12.22}$$

Employing a similar analysis, the optimal price for case 3 can be determined as

$$p^* = \frac{\ln \quad \frac{T}{L \; - N} + 2}{2} \tag{12.23}$$

In order to illustrate the application of the foregoing formulas, we assume the following numerical values for the parameters: $T = 6$ months, $L = 90$, $\beta = 20\%$, and $N = 500$. The optimal price value for three cases can be calculated as follows:

Case 1: $p^* = \dfrac{\ln \;\; \frac{T}{N} + 2}{2} = \dfrac{\ln \;\; \frac{6}{500} + 2}{2} = 0.35$

Case 2: $$p^* = \frac{\ln\dfrac{T}{N-L}+2}{2} = \frac{\ln\dfrac{2}{500-450}+2}{2} = 0.36$$

Case 3: $$p^* = \frac{\ln\dfrac{T}{L\ -N}+2}{2} = \frac{\ln\dfrac{6}{450-500}+2}{2} = 0.32$$

### 12.3.2 Time- and Price- Dependent Demand

In this model, demand varies with time, $t$, and price, $p$, of an item. The product recovery firm (PRF) still faces the four situations outlined in the previous section.

For *Case* 1, the optimal price is obtained by solving $\int_0^T \phi(p,t)dt = N$ for $p$.

For *Case* 2, the optimization problem turns out to involve the standard calculus of variations problem

$$\max_p \int_0^T p\cdot\phi(p,t)\,dt \tag{12.24}$$

subject to

$$\alpha \quad N - \int_0^T \phi(p,t)\,dt \quad \leq L \tag{12.25}$$

Following the procedure outlined in Kamien and Schwartz (1991), the Lagrangian function is $F = p\cdot\phi(p,t) + \eta\cdot\phi(p,t)$, where $\eta$ is the Lagrange multiplier. The Euler equation of $F$ is

$$\frac{\partial F}{\partial p} = (p+\eta)\frac{\partial}{\partial p}\phi(p,t) + \phi(p,t) = 0 \tag{12.26}$$

Solving for $p$, one gets

$$p^* = -\eta - \frac{\phi(p,t)}{\dfrac{\partial}{\partial p}[\phi(p,t)]} \tag{12.27}$$

In Equation (12.27), if $\eta = 0$, then the optimal price is

$$p^* = -\frac{\phi(p^*, t)}{\phi_p(p^*, t)} \tag{12.28}$$

if $\eta > 0$, then the optimal price is

$$p^* \leq -\frac{\phi(p^*, t)}{\phi_p(p^*, t)} \tag{12.29}$$

where $\phi_p = \frac{\partial}{\partial p}$.

For *Case* 3, following the same approach as in *Case* 2, the optimal price is obtained by

$$p^* = \eta - \frac{\phi(p, t)}{\phi_p(p, t)} \tag{12.30}$$

From Equation (12.30), results similar to Equations (12.28) and (12.29) can be obtained for $\eta = 0$ and $\eta > 0$. The sufficiency condition for $p^*$ to be optimal in all three cases is that $p\,\phi\,(p, t)$ be concave.

For *Case* 4, the optimal price from either of the first three cases can be used. It can be observed that the optimal price in all four cases is a function of time. It implies that the PRF has to change its prices at every moving time instant, which is not practically feasible. However, the growth of the Internet and e-commerce is facilitating the implementation of continuous pricing (Bitran and Caldentey, 2003). It can also be observed that $c$ and $n$ have no influence on optimal price in all four cases. This makes the model more convenient for the PRF to implement in practice.

Let $\phi(p, t) = \frac{e^{-2bt}}{p^{2r}}$, where $b > 0$ is the demand elasticity, and $r > 0$ is a constant.

For Case 1:

$$p^* = {\frac{1 - e^{-2bT}}{2bN}}^{\frac{1}{2r}} \tag{12.31}$$

For Case 2:

$$p^* = \frac{-\eta}{1 - \frac{1}{2r}} \tag{12.32}$$

For Case 3:

$$p^* = \frac{\eta}{1 - \frac{1}{2r}} \tag{12.33}$$

In the foregoing equations, $\eta$ is interpreted as the opportunity cost of selling an item from the inventory. The value of this parameter is calculated using the boundary conditions of the price.

In order to illustrate the application of the foregoing formulas, we assume the following numerical values for the parameters: $b = 0.5$, $r = 1.5$, $T = 4$ months, $L = 40$, $\beta = 25\%$, and $N = 200$. The optimal price value for cases 1 and 2 can be calculated as follows:

For Case 1:

$$p^* = \left(\frac{1 - e^{-2bT}}{2bN}\right)^{\frac{1}{2r}} = \left(\frac{1 - e^{-2\cdot 0.5\cdot 4}}{2 \cdot 0.5 \cdot 200}\right)^{\frac{1}{2\cdot 1.5}} = \$0.17 \text{ and Revenue} = 200 \cdot 0.17 = \$34$$

For Case 2:

$$p^* = \frac{-\eta}{1 - \frac{1}{2 \cdot 1.5}} = -\frac{3}{2} \cdot \eta$$

If the initial price at the start of the selling horizon is $p(0) = \$0.3$, then $\eta = -0.2$. So, for *Case* 2, $p^* = \$0.3$ for the selling horizon.

## 12.4 Other Models

Researchers have developed many mathematical models and heuristics for the pricing of cores, remanufactured products, and components. A heuristic is proposed in Guide et al. (2003) for the determination of the optimal acquisition price of used phones and the selling price of remanufactured phones based on the maximization of profit, which is given as the difference between the total revenue and acquisition and remanufacturing costs. In this remanufacturing system, used phones with different quality levels are remanufactured to a single quality level and are sold at a certain price. The selling price of remanufactured products could be completely determined by the acquisition prices of returns since they assume that demand and return flows perfectly match. They also assume that demand is a function of the price. Guide et al.'s (2003) study is extended by Mitra (2007) in the following four ways:

- Acquisition prices are not considered since the manufacturer considered in the study is responsible for the recovery of returned products.
- Remanufactured products are categorized into more than one quality level.
- A probabilistic situation could be where not all items may be sold, and the unsold items may have to be disposed of.
- Demand is a function of price and availability or supply of recovered goods.

Pricing policies of reusable and recyclable components for third-party firms involved in discarded product processing are investigated by Vadde et al. (2007) under strict environmental regulations. Vadde et al. (2010) determine the prices of reusable and recyclable components and the acquisition price of discarded products in a multicriteria environment that involves the maximization of sales revenue and minimization of product recovery costs (viz., disposal cost, disassembly cost, preparation cost, holding cost, acquisition cost, and sorting cost). Qiaolun et al. (2008) determine the collection, wholesale and retail prices, in a closed-loop supply chain by developing game-theory-based models. A comparison of two hulk pricing strategies for an automotive shredder is provided by Qu and Williams (2008) considering constant, increasing, and decreasing trends for ferrous metal and hulk prices. The optimal acquisition price of EOL products and the selling price of remanufactured parts are determined by Karakayali et al. (2007) for the cases of centralized as well as remanufacturer- and collector-driven decentralized channels. Price and return policy in terms of certain market reaction parameters are determined in the model developed by Mukhopadhyay and Setoputro (2004) for e-business. Considering a market where customers differentiate between new and remanufactured products, Debo et al. (2005) investigate the joint pricing and production technology selection problem of an Original Equipment Manufacturer (OEM). Vorasayan and Ryan (2006) find the optimal price and proportion of refurbished products by modeling the sale, return, refurbishment, and resale processes as an open queuing network. Shi et al. (2011) simultaneously determine the selling price, production quantities for brand-new products and remanufactured products, and the acquisition price of used products based on the maximization of profit for a closed-loop system in which a manufacturer satisfies the demand using two channels: manufacturing brand-new products and remanufacturing returns into as-new products.

In some studies, the pricing strategy is determined by considering the competition between an OEM and an independent operator who may intercept product cores produced by OEM to sell the remanufactured products in future periods. In the two-period model proposed by Majumder and Groenevelt (2001), OEM may or may not remanufacture in the second period. Extending Majumder and Groenevelt (2001), Ferrer and Swaminathan (2006) consider a multiperiod setting where the independent operator competes with the OEM in the second period and subsequent periods. After finding closed-form solutions for prices and quantities, an optimum solution region that was numerically explored by Majumder and Groenevelt (2001) is characterized. New-product pricing decisions and recovery strategy of an OEM in a two-period model are investigated by Ferguson and Toktay (2006) by assuming that the OEM has an easier access to the used product, and the average variable cost of remanufacturing increases with the quantity remanufactured. Extending Majumder and Groenevelt (2001) and Ferguson and Toktay (2006), Ferrer and Swaminathan (2010) consider more than two periods with differentiated remanufactured products. Jung and Hwang (2011) develop mathematical models to determine the optimal pricing policies under two cases—cooperation or competition between an OEM and a remanufacturer. The impact of take-back laws and government subsidies on competitive remanufacturing strategy is analyzed by Webster and Mitra (2007) and Mitra and Webster (2008), respectively. A three-stage game is analyzed by Heese et al. (2005). The first two stages involve the analysis of the sequential decisions of two OEMs whether to take back used products. Both firms simultaneously determine the price of their new products as well as the discount offered for returned products in the third stage.

An effective return policy must be determined by a manufacturer for customer satisfaction as well as the timely acquisition of returned products for remanufacturing or recycling activities. An optimal return policy for build-to-order products is determined by Mukhopadhyay and Setoputro (2005) based on profit maximization. Yao et al. (2005) present a game-theory-based methodology to investigate the role of return policy in the coordination of the supply chain. The integrated product returns model proposed by Yalabik et al. (2005) provides logistics and marketing coordination for a retailer servicing two distinct market segments. The role of a Fourth Party Logistics (4PL) as a return service provider is analyzed by Mukhopadhyay and Setaputra (2006). Optimal decision policies for both the seller and the 4PL are also provided in this study.

Investigating the use of remanufacturing as a tool to satisfy the demand arising from secondary markets, Robotis et al. (2005) point out that the reseller can decrease the number of units procured from the advanced market if he or she uses remanufactured products to satisfy the demand form secondary markets.

## 12.5 Conclusions

In this chapter, two models were presented to discuss the pricing issues in remanufacturing. The first model determined the core prices using the concept of geometric Brownian motion. The second model determined component prices considering various cases. An overview of the other remanufacturing-related pricing models was presented in the previous section.

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# 13

# Control Mechanisms

## 13.1 The Issue

In traditional manufacturing systems, there are two types of production control mechanisms, such as a push system and a pull system. In the push system, production occurs according to a predetermined plan, and materials are normally scheduled to arrive at the line according to a materials requirements plan (MRP). The main disadvantage of this system is excess inventory. On the other hand, the pull system aims to increase the agility of the system by reducing inventory levels. This is achieved by allowing production only if there is a demand for the product. Some of the benefits of the pull system include reduction in bottleneck, cycle time, and inventory-carrying costs. Hence, the pull system has a potential to be implemented in a remanufacturing system, especially in a disassembly line where production is labor intensive and products have limited shelf lives, high carrying costs, or need large storage space.

Kanban, a device to signal the need to move raw materials or produce new components from the previous process, is commonly used when implementing the pull mechanism in assembly lines. It is a simple tool to control the inventory level. However, if demand and supply are uncertain, traditional Kanbans have a tendency to fail. Hence, the Kanban system must be modified to deal with the uncertainties associated with a disassembly line.

In this chapter we discuss the details of two modified Kanban systems developed considering the characteristics of disassembly lines. We also compare the performance of these systems with the performance of the push system. Then, a review of other modified Kanban methodologies is presented.

## 13.2 Modified Kanban System for Disassembly

A novel Kanban system called the Modified Kanban System for Disassembly (MODKS) was developed by Gupta and Kizilkaya (2000) for material control and scheduling in a disassembly environment. The various characteristics of MODKS are discussed in the following subsections. A numerical example is provided in order to show the superiority of MODKS over the traditional push system.

### 13.2.1 Working Mechanism

In MODKS, the disassembled component inventories are kept at a minimum. They are limited by the number of disassembly Kanbans (DKs) employed in the system. Additional products are disassembled when there is component demand. Material and Kanban flows in the modified Kanban system for an *N*-station disassembly line are illustrated in Figure 13.1. At each station, there is one processing machine or operator, one input buffer, and two output buffers. Production and withdrawal Kanbans are used to control the material flows in the line. The withdrawal Kanban of a station always flows between the input buffer of that station and the partially disassembled product buffer of its preceding station. The production Kanban of a station circulates only in that station to control disassembly in that station.

There are two types of production Kanbans for the first *N*-1 disassembly stations, such as a disassembly production Kanban for partially disassembled unit (DPKAN) due to demand occurring at the succeeding stations, and a disassembly production Kanban for the disassembled components (DPKAND) to satisfy the demand for individual components at that station. Station *N* has only DPKAND to satisfy the demand for the disassembled components since the product is completely disassembled at that station.

We can distinguish two work-in-process (WIP) inventory types (i.e., type I WIP and type II WIP) in the system. Partially disassembled products anywhere in the system are considered as type I WIP, while disassembled components placed at output buffers of stations are regarded as type II WIP.

The existence of demand at any station triggers a pull action at the preceding station. Therefore, whether there is a need for the preceding station's components or not, one more product will be disassembled, most likely causing the disassembled component buffer of the preceding station to exceed its capacity. On the other hand, if there is no demand for the succeeding station's components, the partially disassembled product buffer for the current station may exceed its capacity. In order to eliminate excess inventory at these buffers, MODKS disposes additional products and/or components (at some cost) when disassembly Kanban capacities are reached.

### 13.2.2 Comparing MODKS with the Push System

In this section, MODKS is compared with the push system under different scenarios in order to prove its usefulness in the disassembly environment. Due to its ability to model complex systems, discrete event simulation is

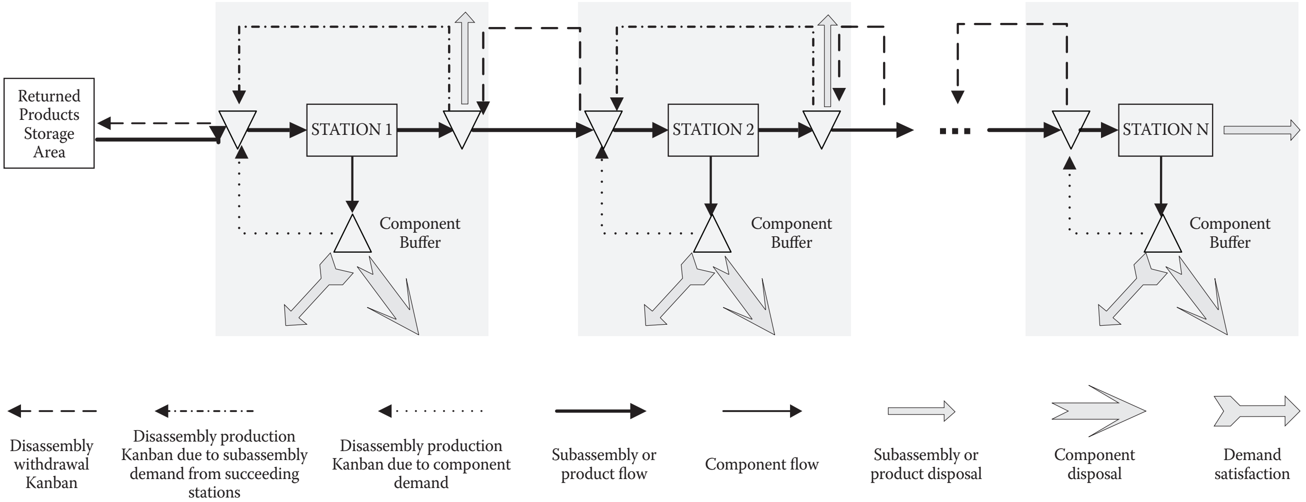

**FIGURE 13.1**
Material and Kanban flows in MODKS.

used to model MODKS and the push system. The following total profit (TP) function is used in simulation experiments.

$$\begin{aligned} TP = {} & \overbrace{\sum_{i=1}^{M}(NCDIS_i \cdot P_i)}^{\text{Revenue from Component Sales}} - \overbrace{\sum_{i=1}^{M}(NCD_i \cdot CD_i)}^{\text{Component Disposal Cost}} - \overbrace{\sum_{i=1}^{M}(NS_i \cdot SC_i)}^{\text{Shortage Cost}} \\ & - \overbrace{\sum_{j=1}^{N}[(NCDIS_j/NC_j)\cdot DISC_j]}^{\text{Disassembly Cost}} \\ & - \underbrace{\sum_{k=1}^{2}[NW_k \cdot H_k]}_{\text{Holding Cost}} - \underbrace{[PD \cdot NPD]}_{\text{Product Disposal Cost}} \end{aligned} \tag{13.1}$$

The components of this function can be explained as follows:

$CD_i$: Unit disposal cost for component type $i$ ($i = 1,2, \ldots, M$).
$PD$: Unit disposal cost for a whole or partially disassembled product.
$DISC_j$: Unit disassembly cost at station $j$ ($j = 1,2, \ldots, N$).
$H_k$: Holding cost per unit of type $k$ WIP per period ($k = 1$ or 2)
$P_i$: Sales price of component type $i$
$SC_i$: Shortage cost for component type $i$
$NCDIS_i$: Number of components disassembled of component type $i$
$NCD_i$: Number of disposed components of component type $i$
$NS_i$: Number short of component type $i$
$NPD_i$: Number of whole or partially disposed products
$NW_k$: Number of type 1 or type 2 WIP
$NC_i$: Number of components per product of component type $i$
$M$: Number of different component types in the product
$N$: Number of stations

In the case example, it is assumed that four part types are disassembled from a product of interest. Product arrivals occur according to Poisson distribution with a mean of 30 products per hour. A capacity of 100 units is assumed for returned products storage area. Part disassembly times for all stations are distributed according to a triangular distribution with a minimum time of 2 minutes, average time of 4 minutes, and maximum time of 6 minutes.

**TABLE 13.1**

Some Characteristics of Parts

| Part Number | Unit Disposal Cost | Multiplicity | Unit Price | Unit Stockout Cost |
|---|---|---|---|---|
| 1 | 0.20 | 4 | 4 | 0.30 |
| 2 | 0.30 | 3 | 6 | 0.40 |
| 3 | 0.40 | 2 | 8 | 0.50 |
| 4 | 0.50 | 1 | 10 | 0.60 |

Disassembly cost per part at any station is \$1.5. Disposal cost of a whole or partially disassembled product is \$4. Unit holding costs of type 1 WIP and type 2 WIP are \$1.4 and \$0.14, respectively. Unit disposal cost, unit price, unit stockout cost, and multiplicity information for each part can be seen in Table 13.1.

The experiments were divided into two groups; group 1 (with relatively high demand for the components), and group 2 (with relatively low demand for the components).

### *13.2.2.1 First Group of Experiments*

For this group of experiments, we assume that the demand rates of the components are distributed according to Poisson distribution with the means of 1.00, 0.50, 0.33, and 0.25 per minute for component types 1, 2, 3, and 4 respectively. We conduct six different experiments consisting of three scenarios of MODKS and three scenarios of the push system. In the MODKS scenarios, the number of Kanbans is set to 1, 2, and 3 for scenarios 1, 2, and 3, respectively. In the push system scenarios, we use input buffer capacities of 8, 11, and 14 units/station for scenarios 4, 5, and 6, respectively, to equate the number of their buffers to that of the MODKS scenarios. In Table 13.2 we use MODKS-$x$ and P-$y$ to represent the six scenarios, where $x$ ($x = 1, 2, 3$) represents the number of Kanbans in MODKS, and $y$ ($y = 8, 11, 14$) represents the input buffer capacities in the push system. In Table 13.2 we summarize the results of the experiments conducted in group 1. The Welch procedure (Law, 2007) is used to confirm the existence of the steady state. In all cases, the steady state is reached well before the 100 days of warm-up period used in all the experiments. The statistics are collected for the next 50 days. The results show that MODKS is superior to the push system in terms of total revenue, amount of disposals, and WIP levels.

### *13.2.2.2 Second Group of Experiments*

For this group of experiments also we assume that the demand rates are distributed according to Poisson distribution but with means of 0.2500, 0.1250, 0.0833, and 0.0625 per minute for component types 1, 2, 3, and 4, respectively. We conduct two different experiments representing one scenario of MODKS

**TABLE 13.2**

Comparison of MODKS and PS for High Demand Rates

| | MODKS-1 | MODKS-2 | MODKS-3 | PS-1 | PS-2 | PS-3 |
|---|---|---|---|---|---|---|
| **Total profit** | $239,450 | $241,652 | $241,540 | $228,964 | $228,465 | $227,629 |
| **Average Type 1 WIP** | 128.16 | 40.98 | 40.74 | 113 | 116 | 119 |
| **Average Type 2 WIP** | 5.39 | 5.77 | 5.83 | 8 | 8.18 | 8.13 |
| **Shortages of Component 1** | 0 | 0 | 206 | 75 | 0 | 24 |
| **Shortages of Component 2** | 0 | 0 | 0 | 0 | 0 | 0 |
| **Shortages of Component 3** | 0 | 0 | 0 | 0 | 0 | 0 |
| **Shortages of Component 4** | 1735 | 1533 | 1462 | 54 | 0 | 8 |
| **Disposed Component 1** | 0 | 33 | 0 | 71 | 140 | 119 |
| **Disposed Component 2** | 1659 | 2170 | 2431 | 5960 | 5994 | 6198 |
| **Disposed Component 3** | 557 | 893 | 1007 | 3940 | 4049 | 4015 |
| **Disposed Component 4** | 0 | 0 | 0 | 0 | 6 | 5 |
| **Disposed Product** | 1137 | 830 | 749 | 5924 | 6043 | 6024 |

and one scenario of the push system (Table 13.3). In the MODKS scenario, the number of Kanbans is set to 2, and in the push system scenario, the buffer capacity of 8 is used (Note that these scenarios are chosen because they are the best performing scenarios in group 1 for MODKS and the push system, respectively).

From the results of this case, we can see that MODKS performs a lot better than the push system (Table 13.3). The disposal rates between the two systems are drastically different, and the total revenue for MODKS is much higher than that for the push system. The MODKS scenario exhibits positive

**TABLE 13.3**

Comparison of MODKS and PS for Low Demand Rates

| | MODKS-2 | PS-8 |
|---|---|---|
| **Total profit** | $16,409 | -$1394.74 |
| **Average Type 1 WIP** | 139 | 113 |
| **Average Type 2 WIP** | 13 | 19 |
| **Shortages of Component 1** | 0 | 0 |
| **Shortages of Component 2** | 0 | 0 |
| **Shortages of Component 3** | 0 | 0 |
| **Shortages of Component 4** | 475 | 0 |
| **Disposed Component 1** | 1316 | 18102 |
| **Disposed Component 2** | 164 | 15073 |
| **Disposed Component 3** | 41 | 10039 |
| **Disposed Component 4** | 0 | 4520 |
| **Disposed product** | 10952 | 6011 |

**TABLE 13.4**

Sensitivity of MODKS-2 and P-8 to Changes in Various Cost Parameters at Low Demand Rates

| Parameters | Delta | Total profit (MODKS-2) | Total profit (PS-8) |
|---|---|---|---|
| Holding Costs | −\$0.05 | \$16,416.00 | −\$1,388.00 |
| Shortage Costs | +\$0.05 | \$16,385.00 | −\$1,394.74 |
| Disposal Costs | −\$0.05 | \$17,032.00 | \$1,292.50 |
| Disposal Costs | −\$0.10 | \$17,656.00 | \$3,980.00 |

revenue, whereas the push system experiences a loss due to high disposal rates and excessive production cost. In terms of shortages in the system, MODKS experiences a shortage of 475 units for component 4 over a 50-day period. Even if this residual demand for component 4 were to be satisfied using new components, MODKS would outperform the push system by avoiding other high costs associated with the push system.

In Table 13.4 we present the results of some additional experiments where the values of disposal, holding, and shortage costs are changed (one at a time) while the values of all other parameters are kept at the same level as in the group 2 experiments. As is clear from Table 13.4, in all cases, MODKS-2 continues to outperform P-8. Note also that MODKS-2 is relatively insensitive to changes in disposal, holding, and shortage costs. However, when shortage costs are low, P-8 shows positive profit albeit quite a bit less than its MODKS-2 counterpart.

From the previous discussion it is clear that MODKS is better than the push system. In order to make disassembly more desirable to the industry, a minimum cost and minimum waste production system should be selected. The numerical example included in this section revealed that, even when the demand rate is high, MODKS outperforms the push system. However, for companies where the demand rate is low, the benefits of MODKS are very significant.

## 13.3 Multikanban System

Udomsawat and Gupta (2008) introduced a novel pull-type disassembly line control system called the multikanban system (MKS), which routes Kanbans in a dynamic way considering the state of the system. The various characteristics of MKS are discussed in the following subsections. Two numerical examples are provided in order to show the superiority of MKS over the traditional push system.

### 13.3.1 Material and Kanban Types

We can distinguish two material types in the system, namely, components and subassemblies. A single item that cannot be further disassembled is called a component. On the other hand, a subassembly is something that can still be disassembled. A subassembly involves at least two components. Both types of materials can be further distinguished as regular or overflow items. Regular items are what customers or downstream workstations demand. In order to fulfill the demand, a server must disassemble the demanded component or subassembly. The residual item from this disassembly process that does not fulfill any request is called an overflow item. Because the disassembly process is initiated by a single Kanban, the residual or overflow item will not have a Kanban attached to it. The overflow item is given priority in being retrieved after it arrives at its buffer. This helps the system eliminate this extra inventory first, which is the result of unbalanced demand.

There are two Kanban types in the system, such as component Kanbans and subassembly Kanbans. A component Kanban is attached to a disassembled component. A subassembly Kanban is attached to a residual subassembly that is placed in the subassembly buffer of the workstation where a component was separated from it. A subassembly is routed to the next workstation according to its disassembly sequence. A component placed in a component buffer can be retrieved by an external demand. Upon receiving the authorization supplied by a subassembly Kanban, a subassembly placed in the subassembly buffer is routed to the next workstation based on its disassembly sequence.

### 13.3.2 Kanban Routing Mechanism

Consider workstation $j$, where $1 \le j \le N{-}1$. When a demand for component $j$ arrives at the component buffer of workstation $j$, one unit of component $j$ is retrieved, and the component Kanban $j$ attached to it is routed to the most desirable workstation. The procedure for determining the most desirable workstation to route the component Kanban $j$ is given below. (Note that this procedure is not applicable to component Kanbans $N$-1 and $N$. In both cases, the Kanbans are routed to the input buffer of the last workstation).

A component Kanban originating from workstation $j$ will be routed to a workstation $i$, where $1 \le i < j$, or workstation $j$, depending on the availability and desirability of the subassembly that contains component $j$. Routing component Kanban $j$ to workstation $i$, where $1 \le i \le (j{-}1)$, will result in an immediate separation of component $j$ from component $i$. Thus, the only subassembly located at the input buffer of workstation $i$ that would be useful is a subassembly that contains only components $i$ and $j$. If this type of subassembly exists in the input buffer of workstation $i$, then workstation $i$ is qualified.

Similarly, if there is at least one subassembly in the input buffer of workstation *j*, then workstation *j* is qualified.

The most desirable workstation, among the qualified ones, to route component Kanban *j* to, such that, if chosen, will cause the least amount of extra inventory in the system, is determined next. Choosing workstation *i* will increase the inventory level of component *i* by an additional unit. Thus, the best workstation *i* is the one that is most starving for its component *ir*. By checking the backorder level of the demand for *i*, we could determine the most starving workstation. If there is a tie, select the most downstream workstation. Choosing workstation *j* will create a residual subassembly that will be further disassembled at downstream workstations. If workstation *j* is chosen, then a proper subassembly must be chosen to disassemble. For example, if a backorder exists at the component buffer of workstation *k*, where $j < k \le (N-1)$, then, if available, we might try to disassemble a subassembly that contains only components *j* and *k*. If more than one workstation qualifies as starving workstations, then the one that is most starving among them is chosen. If there is a tie, then the most downstream workstation is selected. If there is a tie inside a workstation, we break it the same way as a tie inside the upstream workstation. We can now compare the starving levels of workstations *i* and *j*. If the highest starving level of workstation *i* is greater than or equal to the starving level of workstation *j*, then we will route the component Kanban *j* to workstation *i*; otherwise, we will route it to workstation *j*. Note that, whenever an external subassembly is available, it will always be chosen first. Internal subassemblies will only be used when no external subassembly of the desired kind is available. Subassembly Kanbans are routed in a fashion similar to component Kanbans.

### 13.3.3 Determining Kanban Level

The proper flow of components and subassemblies at a desired level throughout the system depends highly on the Kanban level. It can be determined by considering product arrival rate, demand arrival rate, and disassembly time. The following general expressions can be used to calculate the number of Kanbans for both the *component Kanban*, $l_i$, and the *subassembly Kanban*, $l_j^*$:

$$l_i = \max \quad 1, {}^{RR_i}\!\big/_{FR_i} \tag{13.2}$$

$$l_j^* = \max \quad 1, {}^{RR_j^*}\!\big/_{FR_j^*} \tag{13.3}$$

where $RR_i$ is the *request rate* of component *i*, $FR_i$ is the *furnish rate* of component *i*, $RR_j^*$ is the *request rate* of subassembly *j*, and $FR_j^*$ is the *furnish rate* of subassembly *j*. These request rates and furnish rates can be calculated as follows:

$$RR_i = D_i, \quad \text{for} \quad 1 \le i \le n \tag{13.4}$$

$$FR_i = \sum_{t=1}^{i} S_{(i,t)}, \quad \text{for} \quad 1 \le i \le n \tag{13.5}$$

$$RR_j^* = s_i, \ i \text{ is the next component to be disassembled in the sequence} \tag{13.6}$$

$$FR_j^* = a_j^* + \sum_{t=1}^{m-1} S_{(i,t)}, \ i \text{ is the last component to be disassembled in the sequence} \tag{13.7}$$

where $D_i$ is the demand arrival rate of component *i*, $S_{(i,t)}$ is the disassembly rate of component *i* at workstation *t*, $s_j$ is the disassembly rate of subassembly *j*, $a_j^*$ is the arrival rate of subassembly *j* (from external source), *m* is the current workstation index, *n* is the maximum number of components, and *n*–1 is the maximum number of workstations.

For the case of the *component Kanban*, which is requested only from a single source, the request rate is equal to the customer demand arrival rate. However, because the component Kanban arrives from several sources in the system, the furnish rate is the summation of arrival rates from all possible sources. For the case of the *subassembly Kanban*, the furnish rate is influenced by both the disassembly rate and the external subassembly arrival rate. Thus, we take all external and internal arrival rates of subassemblies at the buffer into account. Similarly, the two requesting sources, such as the demand for target component and the demand for residual subassembly, affect the request rate.

### 13.3.4 Numerical Example

We consider a disassembly line with four workstations. The demand for five components are satisfied by disassembling eight different products (ABCDE, ACDE, ABC, AC, BCDE, BC, CDE, and DE). It must be noted that we allow any of the subassemblies to arrive from external sources at the appropriate point on the disassembly line.

A simulation model of the system was constructed using Arena (Kelton et al., 2007). Run time was set to 48 hours after 5 hours of warm-up period for each replication. The steady state was reached and confirmed using the Welch procedure (Law, 2007). Three performance measures (viz., the number of satisfied demand [SD], the average work in process [WIP], and the average order completion time [OCT]) were considered for the push system (PS) and the multikanban system (MKS). Twenty replications of the simulation model were carried out for the PS and MKS cases. Equations 13.2 and 13.3 are used to calculate the Kanban level.

**TABLE 13.5**
Comparison of MKS and Push Systems

| | Component A | | Component B | | Component C | | Component D | | Component E | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **PS** | **MKS** | **PS** | **MKS** | **PS** | **MKS** | **PS** | **MKS** | **PS** | **MKS** |
| **SD** | 471<br>(7.3) | 474<br>(8.7) | 376<br>(6.7) | 379<br>(6.3) | 638<br>(5.8) | 634<br>(7.7) | 474<br>(9.7) | 472<br>(8.9) | 475<br>(6.8) | 473<br>(7.8) |
| **WIP** | 88<br>(5.6) | 16<br>(2.3) | 65<br>(4.9) | 9<br>(1.4) | 129<br>(6.9) | 24<br>(3.9) | 159<br>(7.1) | 35<br>(3.2) | 152<br>(7.3) | 34<br>(3.3) |
| **OCT** | 26.4<br>(2.6) | 26.2<br>(2.1) | 24.9<br>(5.3) | 21.6<br>(3.7) | 38.1<br>(5.7) | 37.8<br>(3.3) | 45<br>(8.3) | 44.7<br>(4.2) | 46.3<br>(8.4) | 45.9<br>(4.7) |

Two sets of experiments representing the push system and the multikanban system are performed. In the push system, all arriving products are processed continuously based on the "first come first served" rule. A summary of average values of the three performance measures with their standard deviations shown in parentheses is presented in Table 13.5. The difference in WIP is statistically significant at 0.05 level since MKS routes the Kanban to the station that always results in the most needed component. This creates the pulling of materials exactly where and when they are needed. The variability in OCT is significantly reduced because MKS allows the disassembly process to start only when there is a demand for a component. This should be helpful when predicting the projected order completion time. Results confirm that MKS is capable of meeting a customer demand that is comparable to the PS. Figure 13.2 shows that MKS has lower average inventory of all five components than the

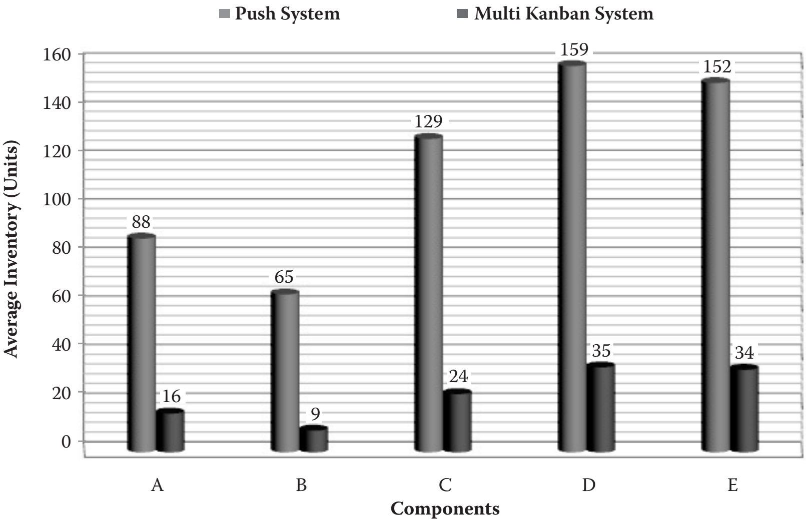

**FIGURE 13.2**
WIP levels for the push system and multikanban system.

PS. The PS builds up inventory in order to fulfill customers' demands. On the other hand, the MKS system deals with fluctuation among demands by routing the Kanbans to the most suitable workstation after determining that there is no overflow part available. By examining the number of parts being requested in real time and the number of available source products, the MKS selects the best destination for the Kanban. In this case, the system is able to reduce the inventory level by an average of 81% while fulfilling customers' demands using the suggested Kanban levels in the system.

### 13.3.5 Numerical Example (Component Discriminating Demand)

End-of-life (EOL) products with different makes, models, and conditions are generally disassembled on the same disassembly line. Different EOL products are needed to retrieve different types of components at different workstations of the disassembly process. There may be multiple types of demand for multiple types of components resulting from the disassembly process at a given workstation. This creates a new scenario called disassembly line with component discriminating demand. The following example exemplifies this scenario.

The numerical example we used to evaluate the multikanban system with component discriminating demand consists of a four-workstation disassembly line. There are at the most five different components in EOL products, such as A, B, C, D, and E. In this study, only products ABCDE, ADC, BCDE, BCE, and CDE are disassembled in sequence. There are two versions of component B ($B_1$ and $B_2$), and three versions of component C ($C_1$, $C_2$, and $C_3$). The versions of component B are disassembled at workstation 2, and the versions of component C are disassembled at workstation 3. Demand interarrival times for component versions are distributed according to Poisson distributions. All service times are exponentially distributed and are the same for all component versions in a workstation. Arena simulation software (Kelton et al., 2007) is used to perform 30 runs of 40 production-hour weeks with warm-up periods of 10 hours considering two scenarios, such as the pull-system using multi-Kanban and the push system.

Statistics on the system's inventory and the number of demands satisfied are collected (see Table 13.6). It is clear that the multikanban system provides comparable number of satisfied demands while carrying a much lower amount of inventory. This is because it minimizes the amount of extra inventory caused by residuals from disassembling a discriminated component.

## 13.3 Other Models

Kizilkaya and Gupta, (2004, 2005a, 2005b, 2006) use discrete event simulation (DES) to test the performance of a novel pull-type disassembly line control mechanism called dynamic Kanban system for disassembly line, which

**TABLE 13.6**

Results

| | Average inventory (units) | | | Satisfied demand (units) | | |
|---|---|---|---|---|---|---|
| | **Push** | **Multikanban** | **% Change** | **Push** | **Multikanban** | **% Change** |
| A | 28 | 5 | −82.1 | 172 | 169 | −1.7 |
| $B_1$ | 62 | 6 | −90.3 | 65 | 66 | +1.5 |
| $B_2$ | 60 | 5 | −91.7 | 61 | 64 | +4.9 |
| $C_1$ | 64 | 6 | −90.6 | 102 | 106 | +3.9 |
| $C_2$ | 62 | 6 | −90.3 | 109 | 104 | −4.6 |
| D | 30 | 5 | −83.3 | 38 | 41 | +7.9 |
| E | 27 | 4 | −85.2 | 37 | 40 | +8.1 |

is based on the flexible Kanban system originally developed by Gupta and Al-Turki (1997) for production environment. The main idea of the mechanism is the dynamic change of the number of Kanbans with respect to the demand and the capacity of the system. Udomsawat and Gupta (2005a, 2005b) analyze the applicability of MKS in the case of multiple precedence relationships and component-discriminating demands, respectively. The effect of server breakdowns on the performance of a disassembly system controlled by MKS is discussed by Udomsawat and Gupta (2005c, 2006).

## 13.4 Conclusions

In this chapter, control mechanisms in remanufacturing systems were discussed by presenting two models. The first model compared the traditional push system with a novel pull-type production control mechanism called the modified Kanban system. A comparison of the traditional push system with another novel pull-type control mechanism called the multikanban system was presented in the second model. In addition, an overview of other modified Kanban models developed for remanufacturing systems was presented in the previous section.

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# 14

# *Uncertainty Management*

## 14.1 The Issue

There is a high level of uncertainty associated with the processing times of remanufacturing operations. The uncertainty in the quantity, quality, and timing of returned products further complicates the analysis of remanufacturing systems. Hence, researchers have developed various models to deal with the uncertainty problem. Based on these models, we can categorize uncertainty in remanufacturing into two main categories: internal uncertainty and external uncertainty. The variations within the remanufacturing process (viz., yield rate, station failures, remanufacturing lead time) are considered as internal uncertainty. External uncertainty arises from the factors outside the remanufacturing process such as the timing, quantity and quality (reusable rate) of the returned products, the timing and level of demand, and procurement lead times of new parts/products.

The first model presented in this chapter deals with internal uncertainty. It analyzes the use of inventory buffers for mitigating internal uncertainty by using a queuing-theory-based heuristic procedure. The second model investigates the potential of sensor-embedded products in coping with internal and external uncertainties in the remanufacturing systems. After that, an overview of the studies analyzing the impact of uncertainty in remanufacturing systems is presented.

## 14.2 Inventory Buffers

Inventory buffers are commonly used in remanufacturing systems to deal with the problems created by internal uncertainty. It is always possible to reduce the effect of internal uncertainties on a remanufacturing cell's performance by increasing the number of buffers at the station that exhibits these shortcomings. However, there is an upper limit on the number of buffers that can be accommodated in the remanufacturing cell due to physical constraints and many other real-life circumstances. For instance, if the number of buffers in the cell is increased, the mean processing time and the WIP inventory through the cell will increase. This increase will negatively affect the operating costs and due-date performance. Hence, the allocation of available buffer space to the stations in an optimal way is a very complex problem. It involves many conflicting objectives such as the minimization of remanufacturing costs and processing times and maximization of the throughput rate. The need for the coordination of the serviceable inventory between remanufactured products and new products further complicates the problem.

Aksoy and Gupta (2005) developed a near-optimal buffer allocation plan for a remanufacturing cell consisting of a queuing network with finite buffers and unreliable servers. The methodology is based on the integration of the decomposition principle and expansion methodology. In the decomposition principle, first, the queuing network is divided into individual nodes in order to analyze and estimate the necessary parameters of each node independent of the rest of the network. Next, the interaction of each node with the other nodes is evaluated. While analyzing each node individually, the expansion methodology is used since it is an efficient tool for the analysis of nodes with finite buffers.

### 14.2.1 Methodology

#### *14.2.1.1 Application of Decomposition and Expansion Principles to the Network*

The network is decomposed, and each node is studied in isolation. Here, $M/M/1(BD)/K_i$ represents an $M/M/1/K_i$ node when the machine at the node is subject to breakdown. Next, the network is conceptually expanded by adding a virtual holding node in front of each node's finite buffer. If the buffer is not full, the arriving job is routed directly to the buffer at node $i$ with probability $1 - P_{Ki}$. If the buffer at node $i$ is full and the job is denied entrance into the node, it is routed to the holding node with probability $P_{Ki}$. The job stays in the holding node until a space becomes available at the buffer of node $i$. During its stay at the holding node, the job checks the status of the buffer of node $i$. It is rerouted back to the holding node with probability $P_{K_i}$ if the buffer is full. The holding node can be considered as an $M/M/\infty$ node with zero processing time. Hence, any number of jobs rejected by the full buffer of node $i$ can be accommodated by the holding node. The job joins the buffer with probability $1 - P_{K_i}$ upon the availability of a space at the buffer of node $i$.

### *14.2.1.2 Calculation of Network Parameters*

The equilibrium equations for $Pqs_i$ (probability that there are $s_i$ $(0 < s_i < K_\mathrm{i})$ jobs at node *i* and the machine is either broken down ($q = 1$) or serving ($q = 0$) can be written as follows:

$$\lambda t_i P_{00_i} = \quad {}_i P_{01_i} \tag{14.1}$$

$$(\lambda t_i + \quad {}_i + \alpha_i) P_{0s_i} = \lambda t_i P_{0,s_i-1} + \quad {}_i P_{0,s_i+1} + \beta_i P_{1,s_i}, \quad 1 \le s_i \le K_i - 1 \tag{14.2}$$

$$(\quad {}_i + \alpha_i) P_{0K_i} = \lambda t_i P_{0,K_i-1} + \beta_i P_{1,K_i} \tag{14.3}$$

$$(\lambda t_i + \beta_i) P_{11_i} = \alpha_i P_{01_i} \tag{14.4}$$

$$(\lambda t_i + \beta_i) P_{1s_i} = \alpha_i P_{0s_i} + \lambda t_i P_{1,s_i-1}, \quad 2 \le s_i \le K_i - 1 \tag{14.5}$$

$$\beta_i P_{1,K_i} = \alpha_i P_{0,K_i} + \lambda t_i P_{1,K_i-1} \tag{14.6}$$

$$P_{10_i} = 0 \tag{14.7}$$

where $\lambda t_i$ is the arrival rate to node *i*, $\alpha_i$ is the breakdown rate of node (station) *i*, $\beta_i$ is the buffer capacity of node *i*, and $\quad_i$ is the service rate at node *i*.

The following expression gives the boundary condition:

$$\sum_{q=0}^{1} \sum_{s_i=0}^{K_i} P_{qs_i} = 1 \tag{14.8}$$

The steady-state solution is obtained by solving the equilibrium equations recursively as follows:

$$P_{01_i} = \frac{\lambda t_i}{\quad_i} P_{00_i} \tag{14.9}$$

$$P_{0s_i} = \frac{\lambda t_i}{\quad_i} \quad P_{0,s_i-1} + \frac{\alpha_i}{\lambda t_i + \beta_i} \sum_{m=1}^{s_i-1} P_{0m} \quad \frac{\lambda t_i}{\lambda t_i + \beta_i}^{\quad s_i-m-1} \quad , \quad 2 \le s_i \le K_i \tag{14.10}$$

$$P_{10_i} = 0 \tag{14.11}$$

$$P_{11_i} = \frac{\alpha_i}{\lambda t_i + \beta_i} P_{01_i} \tag{14.12}$$

$$P_{1s_i} = \frac{\alpha_i}{\lambda t_i + \beta_i} \sum_{m=1}^{s_i} P_{0m} {\frac{\lambda t_i}{\lambda t_i + \beta_i}}^{s_i - m}, \quad 2 \le s_i \le K_i - 1 \tag{14.13}$$

$$P_{1K_i} = \frac{\lambda t_i}{\beta_i} \frac{\alpha_i}{\lambda t_i + \beta_i} \sum_{m=1}^{K_i - 1} P_{0m} {\frac{\lambda t_i}{\lambda t_i + \beta_i}}^{K_i - m - 1} + \frac{\alpha_i}{\beta_i} P_{0K_i} \tag{14.14}$$

$$P_{00_i} = 1 - \sum_{q=0}^{1} \sum_{s_i=1}^{K_i} P_{qs_i} \tag{14.15}$$

The probability that there are $s_i$ jobs in node $i$ ($P_{s_i}$) can be determined as follows:

$$P_{s_i} = P_{0s_i} + P_{1s_i}, \quad 0 \le s_i \le K_i \tag{14.16}$$

Using Equations (14.10) and (14.14), $P_{K_i}$ can be calculated as:

$$P_{K_i} = P_{0K_i} + P_{1K_i} \tag{14.17}$$

The following expressions can be used to approximate the accumulation rate at node $i$ ($\lambda_i$) and the feedback blocking probability ($P_{K_i}$):

$$\lambda_i = \lambda j_i - \lambda h_i (1 - P_{K_i}) + \alpha_i + \beta_i \tag{14.18}$$

$$P_{K_i} = {2 - \frac{\lambda_i \left(r_{2_i}^{K_i} - r_{1_i}^{K_i}\right) - \left(r_{2_i}^{K_i - 1} - r_{1_i}^{K_i - 1}\right)}{{}_i\left(r_{2_i}^{K_i + 1} - r_{1_i}^{K_i + 1}\right) - \left(r_{2_i}^{K_i} - r_{1_i}^{K_i}\right)}}^{-1} \tag{14.19}$$

where $\lambda j_i$ is the arrival rate of those jobs that are not rejected by the cell, and $\lambda h_i$ is the arrival rate of the jobs to the holding node after getting rejected by the full buffer at the destination node.

$$\lambda j_i = \lambda t_i (1 - P_{K_i}) \tag{14.20}$$

$$\lambda h_i = \lambda t_i P_{K_i} \tag{14.21}$$

$$r_{1_i} = \frac{(\lambda_i + 2\quad {}_i) - \sqrt{z_i}}{2\quad {}_i} \tag{14.22}$$

$$r_{2_i} = \frac{(\lambda_i + 2\quad{}_i) + \sqrt{z_i}}{2\quad{}_i} \tag{14.23}$$

$$z_i = (\lambda_i + 2\quad{}_i)^2 - 4\lambda_i\quad{}_i \tag{14.24}$$

### 14.2.1.3 Calculation of Throughput

The throughput of each node ($TH_i$) can be calculated independently since we analyze each node independently and in isolation. The following expression is used to calculate the throughput of node *i* (Gupta and Kavusturucu, 2000).

$$TH_i = (L_i - Lq_i)\quad{}_i + \lambda j_i(1 - P_{K_i})^{\rho_i+\rho_{i-1}}(1 - P_{K_i}) \tag{14.25}$$

where $\rho_i$ is the utilization rate at node *i* ($\lambda t_i/\quad{}_i$).

The throughput equation can be written as follows when the node is branching into *M* parallel paths:

$$TH_i = r_{ij}((L_i - Lq_i)\quad{}_i + \lambda j_i(1 - P_{K_i})^{\rho_i+\rho_{i-1}}(1 - P_{K_i})), \qquad j = 1, 2, \ldots, M \tag{14.26}$$

where $r_{ij}$ is the routing probabilities of remanufacturing operations from node *i* to node *j*.

The throughput equation can be written as follows when *M* parallel paths are merging into a single node:

$$TH_i = \sum_{j=1}^{S}((L_i - Lq_i)\quad{}_i + \lambda j_i(1 - P_{K_i})^{\rho_i+\rho_{i-1}}(1 - P_{K_i})) \tag{14.27}$$

where the expected number of jobs in node *i* are

$$L_i = \sum_{s_i=0}^{K_i} s_i P_{s_i} \tag{14.28}$$

and the expected number of jobs in the queue at node *i* are

$$Lq_i = \sum_{s_i=1}^{K_i}(s_i - 1)P_{0s_i} + \sum_{s_i=1}^{K_i} s_i P_{1s_i} = L_i - \sum_{s_i=1}^{K_i} P_{1s_i} \tag{14.29}$$

It must be noted that the throughput for node *i* becomes the arrival rate for the downstream node. In addition, the throughput of the entire system is equal to the throughput of the last node.

### 14.2.2 Model Formulation

The mathematical model for the optimal buffer allocation problem for a remanufacturing cell can be written as follows:

$$\text{Minimize Total Cost} \tag{14.30}$$

subject to $\sum_{i=1}^{I} K_i = N$

$$K_i \geq 1 \quad \text{and integer} \quad (\forall i = 1,2,\ldots,I)$$

where $I$ is the number of stations in the network.

#### *14.2.2.1 Assumptions*

Assumption of the model can be summarized as follows:

- Return and demand processes are independent.
- Interarrival times for returns (core) and demand are distributed according to exponential distributions with rates $\lambda_{ar}$ and $\gamma$, respectively.
- There is one server at each station.
- The finite buffer capacity of each station is represented by $B_i$.
- The service rate $\mu_i$ for each operation is exponentially distributed.
- The service discipline is First Come First Served (FCFS).
- The breakdown rate $\alpha_i$ and the repair time rate $\beta_i$ for a broken machine at station *i* are exponentially distributed.
- The blocking mechanism in the remanufacturing cell is "block after service (BAS)." In this mechanism, when an item is ready to join a station, the item joins the queue at that station if the buffer at that station is not full. If the buffer is full and the item cannot join the queue, it stays where it originated and blocks that server. A blocked job is released to the downstream station when a space becomes available in its buffer. The only exception is when a used product first arrives to the first station from outside. In that case, if the returned product finds the buffer of the first station full, it cannot enter the remanufacturing cell and is considered lost. A penalty cost is applied in this case due to the potential loss of recoverability from the returned product.

- A remanufactured unit is instantly directed to the serviceable inventory from where the demand is satisfied.
- New products are procured from outside to deal with any shortage.

#### 14.2.2.2 Cost Function

The following types of recovery and remanufacturing costs are considered while calculating the total cost:

- Cost of returned products (cores) to the remanufacturing cell including transportation expenses. This cost is calculated by multiplying the purchase cost per item ($c_p$) by the expected rate of the returned products ($E(R)$). $E(R)$ is equal to the returned product arrival rate ($\lambda_{ar}$).
- Cost of disposed cores. This cost is calculated by multiplying the expected rate of the disposition station ($E(D)$) by the disposal cost per item ($c_d$). $E(D)$ is estimated by the throughput rate of the associated station ($TH_3$).
- Cost of testing the returned products. This cost is calculated by multiplying the expected rate of the testing facility ($E(T)$) by the testing cost per item ($c_t$). $E(T)$ is estimated by the throughput rate of the inspection station ($TH_2$). After inspection, the parts are directed to either the remanufacturing shops with the probability of $r$ or the disposition station with the probability of $(1 - r)$.
- Cost of disassembling the returned products. This cost is calculated by multiplying the expected rate of disassembled products ($E(DS)$) by the disassembly cost per item ($c_{dis}$). The expected rate of disassembled products is estimated by the throughput rate of the associated station ($TH_1$).
- Cost of outside procurement of the new products. This cost is calculated by multiplying the expected rate of outside procurement ($E(OP)$) by the outside procurement cost per item ($c_m$). The expected rate of outside procurement is estimated by the difference in the demand and the return rate ($\gamma - \lambda_{ar} \cdot r$).
- Cost of inventory holding. This cost is calculated by multiplying the expected inventory level for the remanufacturing cell ($E(INV)$) by the on-hand serviceable inventory cost per item ($c_{hs}$). The expected inventory level is estimated by the average queue length of serviceable inventory ($L_{q_7}$).
- Cost of lost sales. This cost is calculated by multiplying the expected rate of lost sales ($E(LS)$) by the cost of loss sale per item ($c_l$). The expected rate of lost sales is estimated by the starving probability of serviceable inventory and the demand rate ($\gamma \cdot P_{07}$).

- Cost of rejecting items due to buffer unavailability. This cost is calculated by multiplying the expected rate of rejected items ($E(REJ)$) by the penalty cost per rejected item ($c_{rej}$). The expected rate of rejected items is estimated by the probability of experiencing full buffer at the first station ($P_{K_1}$)
- Cost of remanufacturing at station *i*. This cost is calculated by multiplying the expected rate of the remanufactured parts at station *i* ($E(REM_i)$) by the remanufacturing cost per item at station *i* ($c_{ri}$). The expected rate of the remanufactured parts at each station is estimated by its throughput rate ($TH_{\mathrm{i}}$).

The expected total cost expression can then be written as:

$$E(TC) = c_p \cdot E(R) + c_d \cdot E(D) + c_t \cdot E(T) + c_{dis} \cdot E(DS) + \sum_{i=1}^{4} c_{ri} \cdot E(REM_i) + c_m \cdot E(OP)$$

$$+ c_{hs} \cdot E(INV) + c_l \cdot E(LS) + c_{rej} \cdot E(REJ) \tag{14.31}$$

#### *14.2.2.3 Heuristic Procedure*

STEP 0

Read in the values of the following parameters and cost variables:

$\lambda_{ar}, N, r, c_d, c_{dis}, c_{hs}, c_l, c_m, c_p, c_{ri}, c_t, c_{rej}$

and $\beta_i, \alpha_i, \mu_i, \forall i\,(i = 1,2,\ldots,I)$.

Set $j = 0$ and BAL (Buffer Allocation List) = { }.

STEP 1

Allocate buffers to stations. Different strategies can be used for the initial allocation of buffers ($k_0$) to various stations. Consideration of the efficiency of each station and associated buffer's priority in the remanufacturing line is one of these strategies. We can express the efficiency of station *i* ($\pi_i$) as (Jeong and Kim, 1997):

$$\pi_i = \frac{{}_i \cdot \alpha_i}{(\alpha_i + \beta_i)} \tag{14.32}$$

Then the priority of station *i*'s buffer ($PR_i$) is defined as follows:

$$PR_i = \sum_{\substack{\text{all}\\ u(i)}} \frac{s_{u(i)} \cdot r_{u(i)}}{\pi_{u(i)}} + \sum_{\substack{\text{all}\\ d(i)}} \frac{s_{d(i)} \cdot r_{d(i)}}{\pi_{d(i)}} \tag{14.33}$$

where $s_{u(i)}$ and $s_{d(i)}$ are the number of buffers at the immediate upstream and the immediate downstream station from station $i$, respectively; $\pi_{u(i)}$ and $\pi_{d(i)}$ are the efficiencies of upstream and downstream stations, respectively; and $r_{u(i)}$ depicts the routing probability from the upstream station to buffer $i$, and $r_{d(i)}$ depicts the routing probability from buffer $i$ to the downstream station. Since each buffer is connected to the single station in our sample network, $r_{(i)}=1$.

To obtain the initial buffer allocation vector ($k_0$), the priority of all stations are normalized, and total number of available buffer slots ($N$) are distributed as follows:

$$K_{i,0} = N\frac{PR_i}{\sum_{i=1}^{I} PR_i}, \forall i(i = 1,2,\ldots,I); \quad K_{i,0} \geq 1, \forall i \tag{14.34}$$

where $x$ denotes the largest integer less than or equal to $x$.

$\bar{k}^* := \bar{k}_0$, and $\bar{k}_0$ is appended to the BAL where $\bar{k}^*$ is the optimal solution.

The rejection rate of the returned products from the cell can be reduced by assigning the remaining buffer slots, if any, to the first station.

STEP 2

Calculate the cell performance parameters ($TC$, $TH_i$, $TH$, and Processing Time ($PT$)) at $k_j$ by utilizing the decomposition principle and the expansion methodology. Note that $PT$ can be calculated using Little's formula as follows:

$$PT = \sum_{i=1}^{I} \quad {}_i + \frac{L_{q_i}}{\lambda t_i} \tag{14.35}$$

STEP 3

Determine the difference between the buffer capacity ($K_{i,j}$) and the average queue length at each station ($L_{i,j}$) to move from the current buffer allocation to a new one ($\bar{k}_j \rightarrow \bar{k}_{j+1}$) as follows:

$$\delta_{i,j} = K_{i,j} - L_{i,j}, \qquad \forall i\ (i = 1,\ldots,I) \tag{14.36}$$

Identify Max ($\delta_{i,j}$) and Min ($\delta_{i,j}$) ($i$=1, …, $I$)

STEP 4

Select a new buffer allocation $\bar{k}_{j+1}$ as follows:

At the station with Max ($\delta_{i,j}$), set $K_{i,j+1} = K_{i,j} - 1$. Similarly, at the station with Min ($\delta_{i,j}$), set $K_{i,j+1} = K_{i,j} + 1$.

*STEP 5*

If TC ($\bar{k}_{j+1}$) < TC ($\bar{k}^*$), and $\bar{k}_{j+1} \notin$ BAL or

If TC ($\bar{k}_{j+1}$) = TC ($\bar{k}^*$) and TH ($\bar{k}_{j+1}$) = TH ($\bar{k}^*$), and $\bar{k}_{j+1} \notin BAL$, then set $\bar{k}^* = \bar{k}_{j+1}$ and $j = j + 1$ and include $\bar{k}_{j+1}$ in the BAL and go to Step 2. Otherwise, go to Step 4 and consider the next Max ($\delta_{i,j}$) and transfer the buffers accordingly.

*Stopping rule:* If the existing optimal solution ($\bar{k}^*$) cannot be improved after a certain number of iterations (predetermined), STOP.

### 14.2.3 Numerical Example

Consider the remanufacturing cell given in Figure 14.1. The values of various parameters associated with this cell are presented in Table 14.1. Upon applying the heuristic procedure, the near-optimal buffer allocation is determined as (2,1,1,1,1,1,1). This buffer allocation results in a throughput value of 0.231 and a total cost value of 32.737.

## 14.3 Sensor-Embedded Products

Suppliers have to comply with strict requirements on the quality, quantity, and arrival time of components in a traditional manufacturing system. However, in remanufacturing, such strict requirements cannot be imposed on the quality, quantity, and arrival time of EOL products. That is why determination of the condition, type, and quantity of a component before actually disassembling it is not possible. This increases the uncertainty associated with the used component yield.

Sensor-embedded products (SEPs), which involve sensors embedded into their critical components during the production process, can solve this problem by providing information on the condition, type, and number of components before actually disassembling them (Wang and Gupta, 2011). In this subsection we analyze the potential of SEPs in coping with the uncertainty associated with the disassembly of components from EOL appliances for remanufacturing. The impact of SEPs on system performance is analyzed by performing separate experimental design studies based on orthogonal arrays for conventional products (CPs) and SEPs. Detailed discrete event simulation (DES) models of both cases are used to calculate various performance measures under different experimental conditions. Then, the results of pairwise t-tests comparing the two cases based on different performance measures are presented.

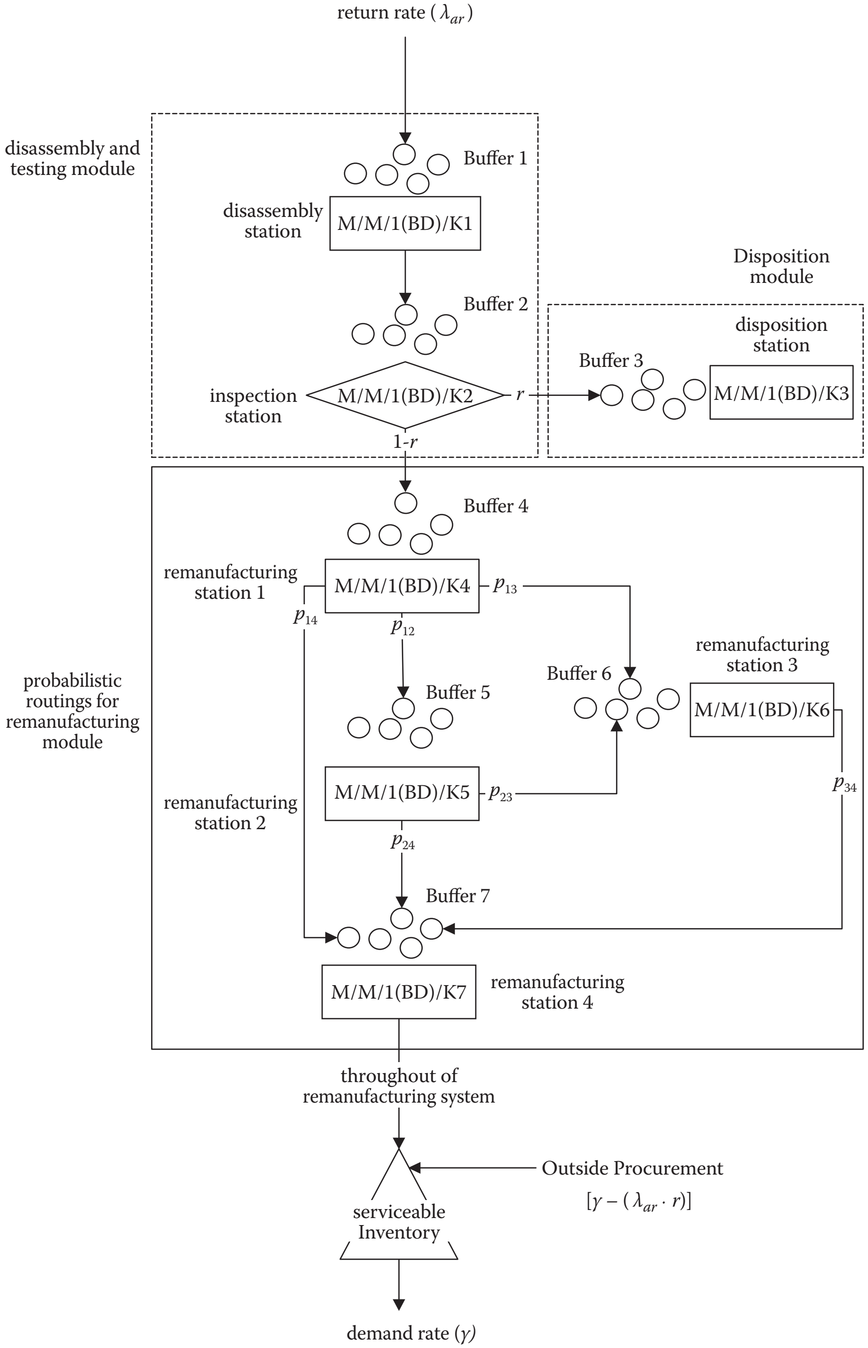

**FIGURE 14.1**
Schematic representation of the remanufacturing cell.

**TABLE 14.1**

Parameter Values

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $\lambda_{ar}$ | 0.9 | $\beta_7$ | 3 |
| $\mu_1$ | 1.2 | $r$ | 0.4 |
| $\alpha_1$ | 0.2 | $N$ | 8 |
| $\beta_1$ | 1 | $c_m$ | 25 |
| $\mu_2$ | 1.8 | $c_p$ | 4 |
| $\alpha_2$ | 0.2 | $c_{dis}$ | 5 |
| $\beta_2$ | 3 | $c_d$ | 5 |
| $\mu_3$ | 1.5 | $c_{r1}$ | 3 |
| $\alpha_3$ | 0.4 | $c_{r2}$ | 2 |
| $\beta_3$ | 2 | $c_{r3}$ | 3 |
| $\mu_4$ | 1.2 | $c_{r4}$ | 1 |
| $\alpha_4$ | 0.4 | $c_{hs}$ | 1 |
| $\beta_4$ | 1 | $c_1$ | 5 |
| $\mu_5$ | 1.5 | $c_{rej}$ | 5 |
| $\alpha_5$ | 0.2 | $c_t$ | 1 |
| $\beta_5$ | 3 | $p_{12}$ | 0.5 |
| $\mu_6$ | 1.2 | $p_{13}$ | 0.4 |
| $\alpha_6$ | 0.2 | $p_{14}$ | 0.1 |
| $\beta_6$ | 2 | $p_{23}$ | 0.8 |
| $\mu_7$ | 1.2 | $p_{24}$ | 0.2 |
| $\alpha_7$ | 0.4 | $p_{34}$ | 1 |

### 14.3.1 System Description

EOL refrigerators and washing machines (WMs) are disassembled on a five-station disassembly line. Components disassembled at different stations of the disassembly line, together with the disassembly sequence and routing of EOL refrigerators and WMs, are presented in Figure 14.2.

There are two common components shared by EOL refrigerators and WMs, such as metal cover and electric motor. Aluminum radiator is only included in refrigerators, while solenoid valve and circuit board are the components that can be disassembled only from EOL WMs. There are customer demands for all disassembled components except for the metal cover. Table 14.2 presents precedence relationships among the components. Disassembly times at stations, demand interarrival times for components, EOL WM, and EOL refrigerator interarrival times are all distributed exponentially.

A multikanban system developed by Udomsawat and Gupta (2008) is used to control the disassembly line.

Conventional appliances (ones with no sensors) visit all stations. Following the disassembly at each station, components are tested. The testing times are normally distributed with means and standard deviations as presented

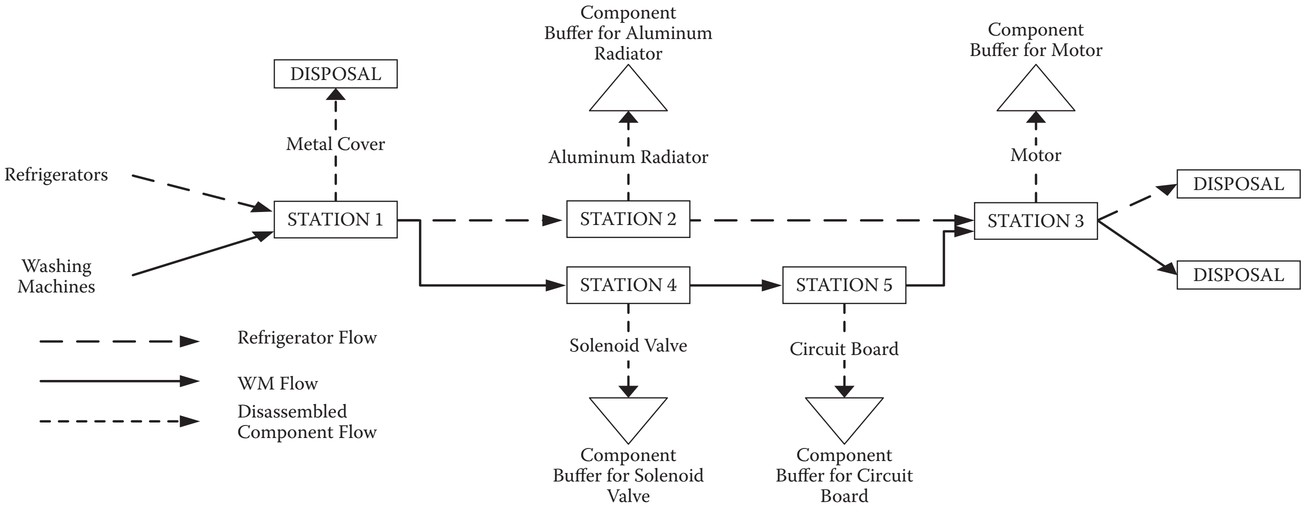

**FIGURE 14.2**
Appliance disassembly line.

**TABLE 14.2**

Precedence Relationships among the Components

| Component name | Code | Precedence Relationship | |
|---|---|---|---|
| | | WM | Refrigerator |
| WM metal cover | A | — | — |
| Refrigerator metal cover | B | — | — |
| Aluminum radiator | C | — | B |
| Motor | D | A,E,F | B,C |
| Solenoid valve | E | A | — |
| Circuit board | F | A,E | — |

in Table 14.3. Sensor-embedded appliances visit only the stations that are responsible for the disassembly of the functional components and their predecessor components. In addition, no testing is required for this case because of the sensor information available on the condition of the component.

Excess products, subassemblies, and components are disposed of using a small truck with a load volume of 475 cft. Whenever the total volume of the excess inventories becomes equal to the truck volume, the truck is sent to a recycling facility. Any product, subassembly, or component inventory that is greater than the *maximum inventory level* is assumed to be excess. Component volumes are given in Table 14.3. The volumes of EOL WMs and EOL refrigerators are taken as 22 cft and 30 cft, respectively.

### 14.3.2 Design of Experiments Study

In this section we compare the SEPs case against the CPs case under different experimental conditions. Table 14.4 presents the factors and factor

**TABLE 14.3**

Component Characteristics

| Component Name | Testing Time (Minutes) | | Volume (cft) | Weight (lb) |
|---|---|---|---|---|
| | Mean | Std. Dev. | | |
| WM metal cover | — | — | 0.72 | * |
| Refrigerator metal cover | — | — | 1.12 | * |
| Aluminum radiator | 6 | 1.5 | 1.13 | * |
| Motor | 12 | 2 | 0.15 | * |
| Solenoid valve | 2.5 | 0.5 | 0.02 | 2.5 |
| Circuit board | 6 | 1 | 0.03 | 0.75 |

*Weights of WM metal cover, refrigerator metal cover, aluminum radiator, and motor are factors in the design of experiment study (see Table 14.4).

**TABLE 14.4**

Factor Levels

| No. | Factor | Levels | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| 1. | Disposal cost increase factor for EOL products | 0.06 | 0.12 | 0.18 |
| 2. | Scrap revenue decrease factor for EOL products | 0.06 | 0.12 | 0.18 |
| 3. | Mean demand rate for radiator *(components per hour)* | 8 | 12 | 16 |
| 4. | Mean demand rate for motor *(components per hour)* | 8 | 12 | 16 |
| 5. | Mean demand rate for solenoid valve *(components per hour)* | 8 | 12 | 16 |
| 6. | Mean demand rate for circuit board *(components per hour)* | 8 | 12 | 16 |
| 7. | Mean arrival rate of EOL WMs *(products per hour)* | 8 | 16 | 24 |
| 8. | Mean arrival rate of EOL refrigerators *(products per hour)* | 8 | 16 | 24 |
| 9. | Mean disassembly time for station 1 *(minutes)* | 0.30 | 0.60 | 0.90 |
| 10. | Mean disassembly time for station 2 *(minutes)* | 0.70 | 1 | 1.3 |
| 11. | Mean disassembly time for station 3 *(minutes)* | 0.70 | 1 | 1.3 |
| 12. | Mean disassembly time for station 4 *(minutes)* | 0.70 | 1 | 1.3 |
| 13. | Mean disassembly time for station 5 *(minutes)* | 0.70 | 1 | 1.3 |
| 14. | Backorder cost rate | 0.35 | 0.55 | 0.75 |
| 15. | Disassembly cost per minute *($)* | 1.2 | 2.4 | 3.6 |
| 16. | Testing cost per minute *($)* | 0.45 | 0.55 | 0.65 |
| 17. | Holding cost rate | 0.15 | 0.25 | 0.35 |
| 18. | Weight for metal cover of WM *(pounds)* | 4 | 7 | 10 |
| 19. | Weight for metal cover of refrigerator *(pounds)* | 5 | 10 | 15 |
| 20. | Weight for radiator *(pounds)* | 2.5 | 5 | 7.5 |
| 21. | Weight for motor *(pounds)* | 4 | 8 | 12 |
| 22. | Weight of other steel components of WM *(pounds)* | 75 | 100 | 125 |
| 23. | Weight of other steel components of refrigerator *(pounds)* | 90 | 110 | 130 |
| 24. | Price of radiator *($)* | 25 | 45 | 65 |
| 25. | Price of motor *($)* | 55 | 80 | 105 |
| 26. | Price of solenoid valve *($)* | 15 | 25 | 35 |
| 27. | Price of circuit board *($)* | 25 | 50 | 75 |
| 28. | Disposal cost per pound *($)* | 0.35 | 0.45 | 0.55 |
| 29. | Steel scrap revenue per pound *($)* | 0.20 | 0.25 | 0.30 |
| 30. | Aluminum scrap revenue per pound *($)* | 0.25 | 0.45 | 0.65 |
| 31. | Maximum inventory level | 6 | 12 | 18 |
| 32. | Small-component weight factor | 0.06 | 0.12 | 0.18 |
| 33. | Probability of a nonfunctional radiator | 0.12 | 0.24 | 0.36 |
| 34. | Probability of a nonfunctional motor | 0.12 | 0.24 | 0.36 |
| 35. | Probability of a nonfunctional solenoid valve | 0.12 | 0.24 | 0.36 |
| 36. | Probability of a nonfunctional circuit board | 0.12 | 0.24 | 0.36 |
| 37. | Probability of a missing radiator | 0.06 | 0.12 | 0.18 |
| 38. | Probability of a missing motor | 0.06 | 0.12 | 0.18 |
| 39. | Probability of a missing solenoid valve | 0.06 | 0.12 | 0.18 |
| 40. | Probability of a missing circuit board | 0.06 | 0.12 | 0.18 |

levels considered in the experiments. A full factorial design with 40 factors requires an extensive number of experiments (viz., 1.22E + 19). Therefore, experiments were performed using orthogonal arrays (OAs) (Aksoy and Gupta, 2005) that allow for the determination of the main effects by running a minimum number of experiments. Specifically, $L_{81}$ OA was chosen since it requires 81 experiments while accommodating 40 factors with three levels (Phadke, 1989). DES models for both cases were developed using Arena 11 (Kelton et al., 2007) to determine the profit value together with various cost and revenue parameters for each experiment. The replication time for each DES model was 60,480 minutes, the equivalent of 6 months with one 8-hour shift per day. DES models were replicated 10 times for each OA experiment.

The following equation presents the formula used in the DES models for the calculation of profit values.

$$Profit = \overbrace{(SR + CR + SCR)}^{\text{Total Revenue}} - \overbrace{(HC + BC + DC + DPC + TC + TPC)}^{\text{Total Cost}} \tag{14.37}$$

where SR is the total revenue generated by component sales during the simulated time period (STP); CR is the total revenue generated by the collection of EOL WMs and refrigerators during the STP; SCR is the total revenue generated by selling scrap components; HC is the total holding cost of components, EOL WMs, EOL refrigerators, and subassemblies during the STP; BC is the total backorder cost of components during the STP; DC is the total disassembly cost during the STP; DPC is the total disposal cost of components, EOL WMs, EOL refrigerators, and subassemblies during the STP; TC is the total testing cost during the STP; and TPC is the total transportation cost during the STP.

In each WM, the metal cover and other steel components are sold as steel scrap. In each refrigerator, the radiator is sold as aluminum scrap, while the metal cover and other steel components are sold as steel scrap. In order to determine the total weight of small components such as screws and cables, the total weight of the main components of a WM or a refrigerator is multiplied by a *small component weight factor.* These small components are considered as waste components. In order to calculate the disposal cost of a waste component, the weight in pounds is multiplied by the *disposal cost per pound*. Disposal cost for subassemblies and products are calculated by multiplying the total weight of waste components in the subassembly or product by the *disposal cost per pound.* The disposal cost of subassemblies and products are increased by a factor called *disposal cost increase factor for EOL products,* considering the fact that disposal of subassemblies and products create higher nuisance levels than components since they may involve multiple and/or hazardous materials.

Scrap revenue for a radiator is calculated by multiplying the weight in pounds by the *aluminum scrap revenue per pound,* whereas scrap revenue for the steel components is calculated by multiplying the weight in pounds by the *steel scrap revenue per pound*. In the calculation of scrap revenue for subassemblies and products, the weight of the radiator existing in the subassembly or product is multiplied by the *aluminum scrap revenue per pound,* whereas the total weight of steel components is multiplied by the *steel scrap revenue per pound.* Scrap revenue for subassemblies and products are decreased by a factor called *scrap revenue decrease factor for EOL products* due to the additional costs associated with further material separation operations that might have to be performed on them before disposal.

The time required to retrieve information from the sensors prior to disassembly is assumed to be 20 seconds and 15 seconds for WMs and refrigerators, respectively, in the estimation of the testing cost for SEPs. While calculating the transportation cost, the operating cost associated with each trip of the truck is assumed to be $55. The collection fee for EOL WMs and EOL refrigerators is $10 per unit.

### 14.3.3 Results

The design of experiments scheme presented in the last section was run for SEPs and CPs. Then, pairwise t-tests were performed for each performance measure. Table 14.5 presents the 95% confidence interval, t-value, and p-value for each test. According to this table, SEPs achieve statistically significant savings in backorder, disassembly, disposal, holding, testing, and transportation costs. Moreover, there are statistically significant improvements in total revenue and profit for the case of SEPs.

**TABLE 14.5**

Pair-wise t-test Results for the Comparison of SEPs against CPs

| Performance measure | 95% Confidence interval on mean difference (sensor–no sensor) | t-value | p-value |
|---|---|---|---|
| Backorder Cost | (−105923.5, −79654.1) | −14.06 | 0.000 |
| Disassembly Cost | (−16248.1, −12916.5) | −17.42 | 0.000 |
| Disposal Cost | (−82426.0, −50567.5) | −8.31 | 0.000 |
| Holding Cost | (−213.777, −158.433) | −13.38 | 0.000 |
| Testing Cost | (−109406, −99502) | −41.98 | 0.000 |
| Transportation Cost | (−40674.3, −37253.7) | −45.34 | 0.000 |
| Total cost | (−339442, −295502) | −28.76 | 0.000 |
| Total revenue | (591931, 758075) | 16.17 | 0.000 |
| Profit | (896733, 1088217) | 20.63 | 0.000 |

## 14.4 Other Models

The impact of uncertainty on the performance of remanufacturing systems is studied by many researchers. A remanufacturer's trade-off between limited information about remanufacturing yields and potentially long supplier lead times is analyzed by Ferrer (2003) and Ferrer and Ketzenberg (2004). According to the results of this study, identification of product yield early in the disassembly process is significantly more valuable than placing purchase orders with a short lead time. The impact of having advanced remanufacturing yield information in long-run average flow time is investigated by Ketzenberg et al. (2003). Extending the just-mentioned three studies, Ketzenberg et al. (2006) consider the uncertainties related to demand, return, and yield while analyzing the value of information in remanufacturing. Extending this study, Ketzenberg (2009) considers a capacitated product recovery system as well as a disposal option for returned products. Inderfurth (2005) investigates the effect of uncertainties related with return, quality, and demand on recovery behavior using numerical analysis.

In Galbreth and Blackburn (2006), optimal sorting and acquisition policies are determined by considering the variability in the condition of used products. The effect of recovery yield information on pricing decisions of a remanufacturer is analyzed by Bakal and Akcali (2006). The effect of uncertainty in quality levels of returned products on the profitability of a single-period refurbishing operation is analyzed by Zikopoulos and Tagaras (2007). An infinite-horizon analysis on the attractiveness of sorting procedures for a single collection center with stochastic yield is investigated by Zikopoulos and Tagaras (2008). A similar analysis is performed by Tagaras and Zikopoulos (2008) for multiple collection centers with deterministic yield. van Wassenhove and Zikopoulos (2010) investigate the impact of quality overestimation on the profit and procurement decisions of a remanufacturer in a single-period setting. Panagiotidou et al. (2011) investigate the benefits of sampling inspection of returns prior to the procurement decision. They also derive analytical expressions and properties for the determination of the optimal sample size and procurement quantity. Aras et al. (2004) analyze the impact of quality-based categorization of returned products by using a Markov chain model. In Behret and Korugan (2009), a DES-based analysis is employed to analyze the effect of quality uncertainties on the performance of a system by considering the classification of returned products based on quality uncertainties. Bakal and Akcali (2006), Aras et al. (2006), and Souza et al. (2002) also study the uncertainty related with the quality of returns.

As an alternative to static modeling, dynamic control methods represent a popular approach to analyzing the effect of uncertainty. In Tang and Naim (2004), the robustness of a push-type hybrid manufacturing/remanufacturing system to various uncertainties of the remanufacturing process is analyzed by performing mathematical and simulation analyses. A similar analysis is performed by Zhou et al. (2006) for a pull-type system. In Zhou and Disney (2006), control theory and simulation is employed for the analysis of the impact of lead time and return rate on inventory variance and the bullwhip phenomenon. In dynamic closed-loop supply chain models developed by Huang et al. (2009), the uncertainty associated with time-delay in remanufacturing and returns, system cost parameters, and customer demand disturbances are considered.

In some studies, the uncertainty in the timing of returns was studied. Atasu and Çetinkaya (2006) investigate the impact of the timing of returns on the cost efficiency of a simple remanufacturing system by developing cost optimization models. The concept of "time value of returns," which involves the use of returns at the best possible time (i.e., whenever suitable market conditions for returns occur), is studied by Guide et al. (2005), Guide et al. (2006), and Geyer et al. (2007).

The use of information technologies (e.g., embedded sensors and RFID tags) in dealing with the high level of uncertainty associated with disassembly yield due to missing and/or nonfunctional components in returned products is another active research area. Vadde et al. (2008) investigate the effectiveness of embedding sensors in computers. Two scenarios (viz., with embedded sensors and without embedded sensors) are compared by considering several performance measures (viz., average life-cycle cost, average maintenance cost, average disassembly cost, and average downtime of a computer). However, a quantitative analysis of the impact of SEPs on these performance measures is not provided. In addition, the disassembly setting does not represent the complexity of a disassembly line since only one component of a computer (hard disk) is considered. As an extension to Vadde et al. (2008), Ilgin and Gupta (2011a) investigate the quantitative impact of SEPs on different performance measures of a disassembly line used to disassemble three components from EOL computers. First, separate designs of experimental studies based on Orthogonal Arrays (OAs) are carried out for conventional products and SEPs. Then, the results of pairwise t-tests comparing the two cases based on different performance measures are presented. The range of monetary resources that can be invested in SEPs is also determined by utilizing the improvements achieved by the SEPs on profit for different experiments. In follow-up studies, Ilgin and Gupta (2010, 2011b, 2011c) present a similar analysis methodology by considering multiple precedence relationships, component discriminating demands, and precedence relationships, respectively. The adaptive knowledge-based system developed by Zhou and Piramuthu (2010) utilizes RFID item-level information for product remanufacturing including inspection, disassembly, and reassembly. A cost-benefit analysis is performed in order to demonstrate the implementability of the proposed system. In Gonnuru (2010), the true condition of the product components is determined by analyzing the data from RFID tags by using a Bayesian approach. A fuzzy logic model is also developed in order to synthesize three input variables (i.e., product usage, component usage, and biographical data) into a solution that maximizes the recovery value while minimizing disassembly costs with an optimal disassembly sequence. The model is solved using genetic algorithms.

## 14.5 Conclusions

In this chapter, uncertainty management in remanufacturing was discussed by presenting two models. The first model used inventory buffers to mitigate the high-level uncertainty associated with remanufacturing systems. In the second model, the potential of sensor-embedded products in dealing with uncertainty in remanufacturing systems was evaluated. The other models of uncertainty management in remanufacturing were reviewed in the previous section.

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# 15

# *Product Acquisition Management*

## 15.1 The Issue

The highly uncertain nature of quantity, quality, and timing of returns requires effective policies for the acquisition of used products. Uncontrolled acquisition of used products results in excessive inventory levels or low customer satisfaction (i.e., stockouts due to insufficient used products). According to Guide and Jayaraman (2000), product acquisition management acts as an interface between reverse logistics activities and production planning and control activities for firms. In this chapter we present two models for product acquisition management. The first model is for the determination of the optimal acquisition quantity, while the second model investigates buyback policy decisions. A review of other product acquisition models is also provided in this chapter.

## 15.2 Determination of Optimal Acquisition Quantity

Consider a firm that tries to determine the acquisition quantity of used items to satisfy a fixed demand of $D$ (Galbreth and Blackburn, 2010). If all returned items are assumed to be in good condition, an acquisition quantity of $D$ will be enough to cover the demand. However, this assumption is not realistic considering the high level of uncertainty associated with item returns. That is why the firm has to acquire additional returned items beyond $D$. By doing this, it can prevent the remanufacturing of returned items that are not in good condition. We will determine the optimum acquisition quantity by considering three different cases of condition variability.

For the sake of analytical tractability, the following three simplifying assumptions are made:

- Item condition is exactly distributed according to $f(\alpha)$, where $\alpha$ values of 0 and 1 represent the best possible and worst possible condition, respectively.
- $f(\alpha)$ is a uniform distribution.

- The relationship between the remanufacturing cost and item condition is linear, and it is represented as $r + \alpha \cdot v$ , where $r$ represents the fixed unit cost while $v$ is a variable cost component that is changing based on the condition of the item.

### 15.2.1 Case 1

In the first case, the condition of each used item is modeled as a real number $\alpha \in [0, 1]$ . Any value taken by this real number is a random variable with a density function of $f(\alpha)$ and a cumulative distribution of $F(\alpha)$.

The cost function can be written as follows:

$$f(Q) = a \cdot Q + (Q - D) \cdot p + r \cdot D + \frac{v \cdot D^2}{2 \cdot Q} \tag{15.1}$$

where

$Q$: Quantity of the used items to be acquired
$D$: Remanufactured item demand
$a$: Acquisition and inspection costs of each used item
$p$: Scrap cost per item
$r$: Fixed portion of remanufacturing cost per item
$v$: Variable portion of remanufacturing cost per item

The first derivative of the cost function is as follows:

$$f\ (Q) = a + p - \frac{v \cdot D^2}{2 \cdot Q^2} \tag{15.2}$$

By equating this first derivative to zero, we find the optimal value of $Q$. In order to get an integer value, we add 0.5 and take the floor function. Using this value, the acquisition quantity that minimizes the total cost can be given as follows:

$$Q^* = \max\ \ D,\ \ D \cdot \sqrt{\frac{v}{2 \cdot (a + p)}} + 0.5 \tag{15.3}$$

#### 15.2.1.1 *Numerical Example*

For a product, acquisition and inspection costs per item is \$50, and there is a \$120 variation in remanufacturing cost depending on the condition of the item. Scrapping cost is \$5 per item. The demand for remanufactured items is 1000. Using these parameter values, the optimal acquisition quantity is

$$Q^* = \max\ \ 1000,\ \ 1000 \cdot \sqrt{\frac{120}{2 \cdot (50 + 5)}} + 0.5 \quad = 1044$$

### 15.2.2 Case 2

In the second case, the condition of each item is explicitly considered to be a uniformly distributed random variable on [0, 1]. Denoting the ordered statistics of $Q$ items, ordered by the condition as $Y_{(1)}, \ldots, Y_{(Q)}$, the remanufacturing cost of the best $D$ items is given by $\sum_{k=1}^{D}[r + v \cdot Y_k]$.

The density function of the $k$th order statistic, $Y_{(k)}$, for uniform distribution is written as

$$Q \cdot \begin{matrix} Q-1 \\ k-1 \end{matrix} \cdot \alpha^{k-1} \cdot (1-\alpha)^{Q-k}; \quad \alpha \in [0,1] \tag{15.4}$$

Using this information, the cost function can be written as

$$f(Q) = a \cdot Q + (Q-D) \cdot p + \sum_{k=1}^{D} r + \int_{0}^{1} Q \cdot \begin{matrix} Q-1 \\ k-1 \end{matrix} \cdot (\nu \cdot \beta) \cdot \beta^{k-1} \cdot (1-\beta)^{Q-k} d\beta \tag{15.5}$$

The acquisition quantity minimizing the total cost is

$$Q^* = \max \; D, \sqrt{\frac{v \cdot D \cdot (D+1)}{2 \cdot (a+p)}} - 0.5 \tag{15.6}$$

#### 15.2.2.1 Numerical Example

Using the parameter values presented in the previous example, $Q^*$ can be determined as follows:

$$Q^* = \max \; 1000, \sqrt{\frac{120 \cdot 1000 \cdot (1000+1)}{2 \cdot (50+5)}} - 0.5 \quad = 1044$$

### 15.2.3 Case 3

In this case, we extend Case 2 by considering nonlinear cost functions. In particular, the remanufacturing cost is modeled as a general nonlinear power function of the item condition. The following total cost equation is provided for a quadratic remanufacturing cost function:

$$f(Q) = a \cdot Q + (Q-D) \cdot p + \sum_{k=1}^{D} r + \int_{0}^{1} Q \cdot \begin{matrix} Q-1 \\ k-1 \end{matrix} \cdot (\nu \cdot \beta^2) \cdot \beta^{k-1} \cdot (1-\beta)^{Q-k} d\beta \tag{15.7}$$

In this case, $Q^*$ can be determined by finding the nearest-integer valued solution to the following equation:

$$Q^* = \frac{(Q+1)^2 \cdot (Q+2)^2}{2 \cdot Q + 3} = \frac{v \cdot D \cdot (D+1) \cdot (D+2)}{3 \cdot (a+p)} \tag{15.8}$$

#### *15.2.3.1 Numerical Example*

Using the parameter values presented in the previous example, $Q^*$ can be determined as follows:

$$Q^* = \frac{(Q+1)^2 \cdot (Q+2)^2}{2 \cdot Q + 3} = \frac{120 \cdot 1000 \cdot (1000+1) \cdot (1000+2)}{3 \cdot (50+5)}$$

$$Q^* = 1130$$

## 15.3 Modeling Buyback Policy Decisions

Some manufacturers provide servicing for their products until they reach the end of their lives and buy the products back for remanufacturing activities. In this policy, the main acquisition planning decision is the determination of the optimum buyback period for used products. We present a mathematical model for this decision based on the hypothesis that acquisition planning is controlled by the service management of the manufacturer and the workplace management of the product user (Mondal and Mukherjee, 2006). The following assumptions are made while developing the model:

- A single product type is considered.
- The effect of interest rates or inflation rate on various costs and revenues is ignored.
- The holding cost associated with product and parts/components is not considered.
- Service cost and buyback price are modeled as deterministic.
- The model is constructed by considering the benefit of the manufacturer (rather than the benefit of the seller of the return who wants to get maximum economic benefit out of using the product).
- Due to the randomness associated with the recovery rate, the remanufacturing cost as well as the revenue collected from the recyclers by selling the nonrecovered parts/components are modeled as stochastic parameters.

The following equation gives the difference between benefits and costs at any instant $t$ ($\delta(t)$):

$$\delta(t) = S_{RC}(.) + S_S(t) - C_B(t) - C_R(.) \tag{15.9}$$

where

$t$: A continuous variable lying between 0 to 1, where $t = 0$ refers to the time when a new unit is sold, and $t = 1$ refers to the end-of-life of the unit

$S_{RC}(.)$: Salvage value from recyclers

$S_S(t)$: Savings from service cost

$C_B(t)$: Buyback price of a unit

$C_R(.)$: Remanufacturing cost per unit

The objective is to determine the value of $t$ for maximizing the function $\delta(t)$. The different components of $\delta(t)$ are expressed as follows:

### 15.3.1 Remanufacturing Cost

An important factor affecting remanufacturing cost is the *recovery rate*, which can be expressed as $\alpha(t) = 1 - \beta t$, where $\beta$ is a strictly positive random variable. The working environment of the unit and the random factors associated with failure possibilities affect the value of $\beta$.

Remanufacturing cost is expressed as a linear function of the recovery rate as follows:

$$C_R(.) = C_f + C_p\beta t \tag{15.10}$$

where

$C_f$: Fixed remanufacturing cost per unit remanufactured

$C_p$: Total cost of new parts/components required to manufacture a new unit

It must be noted that "$C_p\beta t = C_p(1-\alpha)$" is the cost of procurement of parts that cannot be recovered from the return.

### 15.3.2 Buyback Price

Buyback price is expressed as follows:

$$C_B(t) = C_1 - C_2 t \tag{15.11}$$

where

$C_1$: Price of a new unit

$C_2$: Rate of depreciation of value of the product

### 15.3.3 Salvage Value from Recyclers

Salvage value generated by selling off the unusable parts/components to recyclers is expressed as follows:

$$S_{RC}(\alpha) = C_v(1-\alpha) = C_v\beta t \tag{15.12}$$

where
$C_v$: Revenue generated from selling all the parts/components of a unit

### 15.3.4 Savings from Service Cost

The following expression is used to calculate the service cost:

$$C_S(t) = C_s t \tag{15.13}$$

where
$C_s$: Rate of expenditures or use of resources for servicing the unit

The service cost function is integrated over ($t$, 1) in order to determine the savings from the service cost as

$$S_S(t) = \int_t^1 C_s \cdot x\, dx = \frac{C_s}{2}(1-t^2) \tag{15.14}$$

### 15.3.5 Determination and Interpretation of the Optimal Buyback Period

From the foregoing discussion, we can express $\delta(t)$ as

$$\delta(t) = C_2 t - \frac{C_s}{2}t^2 - \beta(C_p - C_v)t + \frac{C_s}{2} - C_1 - C_f \tag{15.15}$$

and its expected value as

$$E(\delta(t)) = C_2 t - \frac{C_s}{2}t^2 - E(\beta)(C_p - C_v)t + \frac{C_s}{2} - C_1 - C_f \tag{15.16}$$

Since the second derivative of $E(\delta(t))$ is less than zero, there is an optimum $t^*$ value that maximizes $E(\delta(t))$. This $t^*$ value can be determined by equating the derivative of $E(\delta(t))$ to 0 and solving for $t$ as follows:

$$t^* = \frac{C_2 - E(\beta)(C_p - C_v)}{C_s} \tag{15.17}$$

The expression for the optimal $t$ value indicates that better servicing by the manufacturers and an efficient workplace environment by the user (including work environment, quality and quantity of consumables, etc.) lengthen the life of a product. This way the product can be used until the value ($C_1$–$C_2$) becomes very low and more parts/components can be recovered for reuse. Hence, the higher value of $C_2$ and the lower value of $(C_p - C_v)$ lead to better service effectiveness. Exploiting this fact, an index called service effectiveness can be written as follows:

$$\textit{Service Effectiveness (SE)} = \textit{Recoverability Index (RI)} \times \textit{Service Index (SI)} \tag{15.18}$$

where *RI* shows the expected recovery value that can be obtained from the available value of the product during its useful life. *SI* can be interpreted as the ratio of the economic value and the rate of service expenditure ($C_s$) spent for the creation of this value.

It must be noted that a lower $E(\beta)$ resulting from better user management leads to a higher recovery index value. On the other hand, the company can control the value of SI by providing efficient servicing activities. The mathematical expressions associated with these three indices can be written as follows:

$$SE = \frac{C_2 - E(\beta)(C_p - C_v)}{C_s} \tag{15.19}$$

$$RI = \frac{C_2 - E(\beta)(C_p - C_v)}{C_2} \tag{15.20}$$

$$SI = \frac{C_2}{C_s} \tag{15.21}$$

### 15.3.6 Numerical Example

In this section we provide a numerical example to illustrate the implementation of the foregoing expressions. Table 15.1 presents the numerical values for $C_p$, $C_v$, and $C_2$.

**TABLE 15.1**

Values of Some Parameters

| Parameter | Value |
|---|---|
| $C_p$ | 1200 |
| $C_v$ | 2 |
| $C_2$ | 2000 |

**TABLE 15.2**

Values of Optimal Buyback Time and Other Indices for Different Values of $C_s$ and $E(\beta)$

| $C_s$ | $E(\beta)$ | $t^*$ | $SE$ | $RI$ | $SI$ |
|---|---|---|---|---|---|
| 1000 | 1.00 | 0.802 | 0.802 | 0.401 | 2 |
| 1000 | 0.90 | 0.9218 | 0.9218 | 0.4609 | 2 |
| 1000 | 0.80 | 1.0416 | 1.0416 | 0.5208 | 2 |
| 1500 | 1.00 | 0.53467 | 0.53467 | 0.401 | 1.33333 |
| 1500 | 0.90 | 0.61453 | 0.61453 | 0.4609 | 1.33333 |
| 1500 | 0.80 | 0.6944 | 0.6944 | 0.5208 | 1.33333 |
| 2000 | 1.00 | 0.401 | 0.401 | 0.401 | 1 |
| 2000 | 0.90 | 0.4609 | 0.4609 | 0.4609 | 1 |
| 2000 | 0.80 | 0.5208 | 0.5208 | 0.5208 | 1 |
| 2500 | 1.00 | 0.3208 | 0.3208 | 0.401 | 0.8 |
| 2500 | 0.90 | 0.36872 | 0.36872 | 0.4609 | 0.8 |
| 2500 | 0.80 | 0.41664 | 0.41664 | 0.5208 | 0.8 |

Our aim is to investigate the impact of two factors (viz., service intensity and working environment at the user's end) on optimal values of the buyback period and other indices. The first factor is represented with $C_s$, and the second factor is represented with the expected value of β. Four values (i.e., \$1,000, \$1,500, \$2,000, \$2,500) are considered for $C_s$, while $E(\beta)$ takes three values (i.e., 1.00, 0.90, 0.80). Table 15.2 presents the optimal buyback period and the values of various indices. The following insights can be inferred from Table 15.2:

- As both *RI* and *SI* indices increase, the optimal buyback period is delayed.
- Lower service efficiency (i.e., lower *SI*) is achieved when the service investment is higher (i.e., higher $C_s$) with the same recovery.
- Optimal buyback period is delayed and higher *RI* is achieved when non-recovery (i.e. $E(\beta)$) is lower.

## 15.4 Other Models

The market driven system and the waste stream system are the two most commonly used product acquisition systems (Guide and Pentico, 2003; Guide and Van Wassenhove, 2001). In a market driven system, financial incentives are employed to encourage users to return their products to the firm. On the other hand, in the waste stream system, firms encouraged by legislation passively accept all product returns from the waste stream.

There are various types of financial incentives used by firms in a market-driven system such as deposit systems, cash paid for a specified level of quality, and credit toward a new unit (Guide and Van Wassenhove, 2001). Several models were developed to investigate the impact of these incentives. Implementation of buyback programs in the power-tools industry was studied by Klausner and Hendrickson (2000). In Guide and Van Wassenhove (2001), the implementation of a quality-dependent incentive policy in which predetermined prices are offered for products with a specific nominal quality level is illustrated by presenting a real-life case study. The optimal incentive values are determined by Guide et al. (2003), Aras and Aksen (2008), and Aras et al. (2008) for a quality-dependent incentive policy. As an extension to Aras et al. (2008), Aksen et al. (2009) consider a government-subsidized collection system. The deposit refund system investigated by Wojanowski et al. (2007) involves the payment of a certain deposit at the time of purchase, which is refunded upon the return of the used product. Considering stochastic demand and partial substitution between original and remanufactured products, Kaya (2010) determines the optimal incentive value.

Seven different types of closed-loop relationships (viz., ownership-based, service contract, direct-order, deposit-based, credit-based, buyback, and voluntary-based) for the acquisition of used products are investigated by Ostlin et al. (2008).

## 15.5 Conclusions

In this chapter, two models were presented on product acquisition management. In the first model, the optimal product acquisition quantity was determined. The second model investigated buyback policy decisions. A review of the studies from the current literature of product acquisition management was also presented in this chapter.

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# 16

# *Supplier Evaluation*

## 16.1 The Issue

Besides used parts disassembled from returned products, new parts are also used in the remanufacturing process. A remanufacturer has to determine the appropriate suppliers for the procurement of new parts. This decision involves the simultaneous consideration of many factors (viz., price, quality, proximity, etc.). That is why multicriteria decision-making methodologies are usually applied to a supplier evaluation problem. In this chapter, we present a multicriteria decision-making methodology integrating the analytic hierarchy process and Taguchi loss functions for supplier evaluation. In addition, a review of other supplier evaluation models is provided in this chapter.

## 16.2 AHP–Taguchi Loss Function–Based Methodology

The multicriteria decision-making methodology of supplier evaluation presented in this section integrates the analytic hierarchy process and Taguchi loss functions in order to rank alternative suppliers (Pi and Low, 2006). The steps of the methodology are as follows:

*Step 1: AHP is employed to obtain the weights of all the decision criteria* (see Section 2.3).

*Step 2*: Quality loss associated with a criterion for a supplier is calculated using the appropriate Taguchi loss function (see Section 2.2).

*Step 3*: Weighted loss of each supplier is calculated using the following equation:

$$WL_j = \sum_{i=1}^{n} W_i \cdot L_{ij} \tag{16.1}$$

**TABLE 16.1**

Comparative Importance Values

| Criteria | Price | Promptness | Defect Rate | Lead Time | Proximity | Eigenvalue Vector |
|---|---|---|---|---|---|---|
| Price | 1 | 2 | ½ | 3 | 5 | 0.333774 |
| Promptness | 1/2 | 1 | 1 | 1 | 2 | 0.135282 |
| Defect rate | 2 | 1 | 1 | 3 | 4 | 0.291971 |
| Lead time | 1/3 | 1 | 1/3 | 1 | 3 | 0.174599 |
| Proximity | 1/5 | ½ | ¼ | 1/3 | 1 | 0.064374 |

where $WL_j$ is the weighted loss of supplier $j$, $W_i$ is the weight of criterion $i$ (determined in step 1) and $L_{ij}$ is the Taguchi loss of criterion $i$ of supplier $j$ (determined in step 2). The supplier with the smallest weighted loss is the best supplier (Pi and Low, 2006).

We illustrate the steps of this methodology with a numerical example. Five criteria (viz., price, promptness, defect rate, lead time, and proximity) are considered in this example.

*Step 1:* The comparative importance values and the normalized eigenvalue vector of the criteria are given in Table 16.1. In this table, the relative impacts given by the decision maker to the criteria are represented with the normalized eigenvalue vector. The pairwise comparisons shown in Table 16.1 are consistent since *CR* value is equal to 0.058.

*Step 2:* Various specifications for the criteria are given in Table 16.2. According to this table, we can illustrate the calculation of Taguchi losses for each criterion as follows:

- *Defect rate*: The target defect rate/breakage probability is zero at which there is no loss to the manufacturer and the upper specification limit for the defect rate/breakage probability is 15%, at which there is a 100% loss to the manufacturer.
- *Promptness*: Loss will incur if the products are delivered late or they are delivered before the scheduled date. The specification limit is 5 days for early and delayed delivery. According to this specification,

**TABLE 16.2**

Various Specifications for Decision Criteria

| Criteria | Target Value | Range | Specification Limit |
|---|---|---|---|
| Price | Lowest | 0–25% | 25% higher |
| Promptness | 0 | 0–5 | 5 |
| Defect rate | 0 | 0–15% | 15% |
| Lead time | Shortest | 0–50% | 50% higher |
| Proximity | Closest | 0–40% | 40% higher |

**TABLE 16.3**

Characteristic and Relative Values of Criteria for Each Supplier

| | Price | | Promptness | | Defect Rate | | Lead Time | | Proximity | |
|---|---|---|---|---|---|---|---|---|---|---|
| Supplier | Value | Relative Value | Value | Relative Value | Value | Relative Value | Value | Relative Value | Value | Relative Value |
| 1 | 120 | 20% | 2 | 2 | 12% | 12% | 5 | 0% | 6 | 20% |
| 2 | 100 | 0% | 4 | 4 | 10% | 10% | 6 | 20% | 8 | 60% |
| 3 | 115 | 15% | 1 | 1 | 7.5% | 7.5% | 7 | 40% | 5 | 0% |
| 4 | 105 | 5% | 5 | 5 | 6% | 6% | 6 | 20% | 7 | 40% |
| 5 | 116 | 16% | 3 | 3 | 9% | 9% | 8 | 60% | 9 | 80% |

100% loss will occur if the delivery is done with a 5 days' delay or if the delivery is done 5 days earlier.

- *Proximity:* The closest supplier has a zero loss. Since the specification limit is up to 40% of the closest supplier, the manufacturer will incur 100% loss when a supplier's distance reaches this specification limit.
- *Price*: The supplier offering the lowest price will have a zero loss. Since the specification limit is 25% higher, the manufacturer will incur 100% loss when a supplier offers a price that is 25% higher than the lowest price.
- *Lead time*: The supplier with the shortest lead time will have a zero loss. Since the specification limit is 50% higher, the manufacturer will incur 100% loss when a supplier has a lead time which is 50% higher than the shortest lead time.

Computing the value of loss coefficient, $k$, using appropriate equations (2.1), (2.2), or (2.3) gives a value of 1600, 4, 4444.4, 400, and 625 for price, promptness, defect rate, lead time, and proximity, respectively.

The characteristic and relative values for each supplier are summarized in Table 16.3. Table 16.4 shows the Taguchi losses for each criterion calculated from the appropriate loss functions for the individual suppliers.

**TABLE 16.4**

Characteristic Taguchi Losses for Each Supplier

| Supplier | Price | Promptness | Defect Rate | Lead Time | Proximity |
|---|---|---|---|---|---|
| 1 | 64 | 16 | 64 | 0 | 25 |
| 2 | 0 | 64 | 44.44 | 16 | 225 |
| 3 | 36 | 4 | 25 | 64 | 0 |
| 4 | 4 | 100 | 16 | 16 | 100 |
| 5 | 40.96 | 36 | 36 | 144 | 400 |

**TABLE 16.5**

Ranking Suppliers Based on Weighted Taguchi Loss Values

| Supplier | Weighted Loss | Normalized Weighted Loss | Supplier Ranking |
|---|---|---|---|
| 1 | 43.821542 | 0.196974 | 4 |
| 2 | 38.910973 | 0.174902 | 3 |
| 3 | 31.030603 | 0.139480 | 2 |
| 4 | 28.765816 | 0.129300 | 1 |
| 5 | 79.944347 | 0.359344 | 5 |

*Step 3:* Weighted Taguchi loss value for each supplier is calculated using Equation (16.1). Weighted and normalized weighted Taguchi loss values are presented in Table 16.5. According to this table, the best supplier is supplier 4.

## 16.3 Other Models

Many multicriteria models have been developed by researchers for supplier evaluation. The most commonly used techniques include analytic hierarchy process, analytic network process, data envelopment analysis, case-based reasoning, fuzzy set theory, and goal programming. Comprehensive reviews of the application of these techniques in supplier evaluation are provided by Aissaoui et al. (2007) and Ho et al. (2010).

A recent trend in supplier evaluation is the consideration of environmental factors. Handfield et al. (2002) presented an AHP application for the evaluation of suppliers based on twenty environment-related criteria. Lee et al. (2009) proposed a fuzzy extended AHP model to evaluate green suppliers for an anonymous TFT–LCD manufacturer in Taiwan. Humphreys et al. (2003) developed a decision support system that integrates environmental criteria into the supplier selection process. The proposed decision support system is also computerized in order to provide a fast and convenient tool for the users to assess their suppliers' environmental performance. Bai and Sarkis (2010) integrate rough set and grey system theory to include environmental factors in supplier evaluation process.

## 16.4 Conclusions

In this chapter, a model of supplier evaluation was presented. The model helps decision makers rank suppliers based on multiple criteria. It integrated AHP and Taguchi loss functions in a three-step procedure. In addition, an overview of other supplier evaluation models was also presented in this chapter.

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# 17

# *Optimal Supplier Portfolio*

## 17.1 The Issue

Acquisition of end-of-life (EOL) products in the right quantities and at the right time is an important goal in remanufacturing. Once the EOL products have been obtained, they can be disassembled into individual components and subassemblies in order to satisfy the different demands. Since EOL products are received in a variety of conditions and from a number of sources, the acquisition process involves a lot of uncertainties. Multiple suppliers offering a wide variety of EOL products, suppliers offering discount rates on the total purchase to increase their competitiveness, independent outside suppliers offering ready-to-use components, capacity limits on the number of components that can be carried into inventory from one period to the next, and stochastic component yields are examples of the uncertainties that may exist.

In this chapter, we focus on the supplier-related uncertainties in the acquisition process. In the first model, the number of EOL products to be purchased from each supplier offering different discount rates based on purchase quantity is determined using nonlinear programming. The second model integrates Taguchi loss functions, AHP, and fuzzy programming. Qualitative evaluation of suppliers is carried out using Taguchi loss functions and AHP. Then fuzzy programming is employed to determine the purchase quantities from each supplier. An overview of the studies in optimal supplier portfolio is also presented in this chapter.

## 17.2 First Model (Nonlinear Programming)

This section presents a nonlinear programming model for the determination of the best combination of EOL products to be purchased, based on the maximization of the total profit and satisfaction of the demand.

### 17.2.1 Revenue and Cost Functions

The total profit value ($Z$) is a function of all the revenue and cost functions in the system. There are two types of revenues: reuse revenue ($R_{RU}$) and recycle revenue ($R_{RC}$). There are six types of costs: total purchase cost ($C_{PEOL}$), total disassembly cost ($C_{DSY}$), total inventory cost ($C_{INV}$), total component procurement cost ($C_{PC}$), total recycle cost ($C_{RC}$), and total disposal cost ($C_{DIS}$).

#### *17.2.1.1 Revenue from the Sale of Reused Components ($R_{RU}$)*

$R_{RU}$ can be calculated from the demand of reuse component $l$ ($D_l^{ru}$) and the unit sale price of component $l$ ($s_l^{ru}$). The mathematical function for $R_{RU}$ can be written as follows:

$$R_{RU} = \sum_l D_l^{ru} \cdot s_l^{ru} \tag{17.1}$$

#### *17.2.1.2 Revenue from the Sale of Recycled Components ($R_{RC}$)*

$R_{RC}$ can be calculated from the demand of recycle component $l$ ($D_l^{rc}$) and the unit sale price of component $l$ ($s_l^{rc}$). The mathematical function for $R_{RC}$ can be written as follows:

$$R_{RC} = \sum_l D_l^{rc} \cdot s_l^{rc} \tag{17.2}$$

#### *17.2.1.3 Cost Associated with the Purchase of End-of-Life (EOL) Products ($C_{PEOL}$)*

$C_{PEOL}$ is a function of the number of EOL product $i$ purchased from supplier $j$ ($Q_{ij}^{EOL}$) and the purchase price of EOL product $i$ from supplier $j$ ($p_{ij}$). The mathematical function for $C_{PEOL}$ can be written as follows:

$$C_{PEOL} = \sum_i \sum_j \left(Q_{ij}^{EOL} \cdot p_{ij}\right) \tag{17.3}$$

In this model, discount rates from supplier $j$ ($DR_j$) are offered on the total dollar amount spent. Therefore, the final total purchase function can be written mathematically as follows:

$$\sum_j ((1 - DR_j) \cdot C_{PEOL\,j}) \tag{17.4}$$

#### *17.2.1.4 Cost of Disassembling End-Of-Life (EOL) Products ($C_{DSY}$)*

$C_{DSY}$ is a function of the total nondestructive disassembly cost ($C_{NDSY}$) and the total destructive disassembly cost ($C_{DDSY}$). $C_{NDSY}$ is a function of the quantity of nondestructive disassembly components *l* ($Q_l^{ndsy}$) and the nondestructive disassembly cost of component *l* ($ndsyc_l$). The $C_{DDSY}$ is a function of the quantity of destructive disassembly components *l* ($Q_l^{ddsy}$) and the destructive disassembly cost for component *l* ($ddsyc_l$). The mathematical functions for $C_{DSY}$, $C_{NDSY}$ and $C_{DDSY}$ can be written as follows:

$$C_{DSY} = C_{NDSY} + C_{DDSY} \tag{17.5}$$

$$C_{NDSY} = \sum_l Q_l^{ndsy} \cdot ndsyc_l \tag{17.6}$$

$$C_{DDSY} = \sum_l Q_l^{ddsy} \cdot ddsyc_l \tag{17.7}$$

#### 17.2.1.5 Cost of Holding Inventory ($C_{INV}$)

$C_{INV}$ is a function of the quantity of ending inventory of components *l* ($Q_l^{Inv}$) and the inventory cost of component *l* ($invc_l$). The mathematical function for the $C_{INV}$ can be written as follows:

$$C_{INV} = \sum_l \left(Q_l^{inv} \cdot invc_l\right) \tag{17.8}$$

#### 17.2.1.6 Cost Associated with the Purchase of Components ($C_{PC}$)

$C_{PC}$ is a function of the quantity of procured components *l* ($Q_l^{pr}$) and the procurement cost of component *l* ($prc_l$). The $Q_l^{pr}$ is equal to the reuse procurement quantity of components *l* ($Q_l^{rupr}$) plus the recycle procurement quantity of components *l* ($Q_l^{rcpr}$). The mathematical functions for the $Q_l^{pr}$ and $C_{PC}$ can be written as follows:

$$Q_l^{pr} = Q_l^{rupr} + Q_l^{rcpr} \tag{17.9}$$

$$C_{PC} = \sum_l \left(Q_l^{pr} \cdot prc_l\right) \tag{17.10}$$

#### 17.2.1.7 Cost of Recycling Components ($C_{RC}$)

$C_{RC}$ is a function of the total in-plant recycling cost ($C_{IRC}$) and the total out-plant recycling cost ($C_{ORC}$). $C_{IRC}$ is a function of the quantity of in-plant recycling of components *l* ($Q_l^{irc}$) and the in-plant recycling cost of component *l* ($ircc_l$). The $C_{ORC}$ is a function of the quantity of out-plant recycling of components $l$ ($Q_l^{orc}$) and out-plant recycling cost of component $l$ ($orcc_l$). The mathematical functions for $C_{RC}$, $C_{IRC}$ and $C_{ORC}$ can be written as follows:

$$C_{RC} = C_{IRC} + C_{ORC} \tag{17.11}$$

$$C_{IRC} = \sum_l Q_l^{irc} \cdot ircc_l \tag{17.12}$$

$$C_{ORC} = \sum_l Q_l^{orc} \cdot orcc_l \tag{17.13}$$

#### *17.2.1.8 Cost of Disposing Components ($C_{DIS}$)*

$C_{DIS}$ is a function of the quantity of disposed components $l$ ($Q_l^{dis}$) multiplied by the disposal cost of component $l$ ($dpc_l$) plus the quantity of bad destructive (hazardous) disassembled components $l$ ($Q_l^{bdda}$) multiplied by the hazardous disposal cost of component $l$ ($hdpc_l$). The mathematical function for $C_{DIS}$ can be written as follows:

$$C_{DIS} = \sum_l \left( \left( Q_l^{dis} \cdot dpc_l \right) + \left( Q_l^{bdda} \cdot hdpc_l \right) \right) \tag{17.14}$$

### 17.2.2 Constraints

The quantity of disassembled components $l$ ($Q_l^{dsy}$) is equaled to the quantity of EOL product $i$ from supplier $j$ ($Q_{ij}^{EOL}$) multiplied by the number of components $l$ in product $i$ from supplier $j$ ($Num_{ijl}$). The mathematical function for the $Q_l^{dsy}$ can be written as follows:

$$Q_l^{dsy} = \sum_i \sum_j \sum_l \left( Q_{ij}^{EOL} \cdot Num_{ijl} \right) \tag{17.15}$$

The quantity of nondestructive disassembled components $l$ ($Q_l^{ndsy}$) is equaled to the quantity of EOL product $i$ from supplier $j$ ($Q_{ij}^{EOL}$) multiplied by the number of components $l$ in product $i$ from supplier $j$ ($Num_{ijl}$) multiplied by the disassembly yield of components $l$ in product $i$ from supplier $j$ ($yld_{ijl}$). The mathematical function for the $Q_l^{ndsy}$ can be written as follows:

$$Q_l^{ndsy} = \sum_i \sum_j \sum_l \left( Q_{ijl}^{EOL} \cdot Num_{ijl} \cdot yld_{ijl} \right) \tag{17.16}$$

The quantity of good nondestructive disassembled components $l$ ($Q_l^{gndsy}$) is equaled to the quantity of nondestructive disassembled components $k$ in period $l$ ($Q_l^{ndsy}$) multiplied by the reuse percentage of components $l$ ($PCT_l^{ru}$). The mathematical function for the can be written as follows:

$$Q_l^{gndsy} = \sum_l \left( Q_l^{ndsy} \cdot PCT_l^{ru} \right) \tag{17.17}$$

The quantity of bad nondestructive disassembled components $l$ ($Q_l^{bndsy}$) is equaled to the quantity of nondestructive disassembled components $l$ ($Q_l^{ndsy}$) subtracted by the quantity of good nondestructive disassembled components $l$ ($Q_l^{gndsy}$). The mathematical function for the $Q_l^{bndsy}$ can be written as follows:

$$Q_l^{bndsy} = \sum_l \left( Q_l^{ndsy} - Q_l^{gndsy} \right) \tag{17.18}$$

The quantity of reuse components $l$ ($Q_l^{ru}$) is equal to the quantity of starting inventory of components $l$ ($Q_l^{SInv}$) plus the quantity of good nondestructive disassembled components $l$ ($Q_l^{gndsy}$) plus the reuse procurement quantity of components $l$ ($Q_l^{rupr}$). The mathematical function for the $Q_l^{ru}$ can be written as follows:

$$Q_l^{ru} = \sum_l \left( Q_l^{SInv} + Q_l^{gndsy} + Q_l^{rupr} \right) \tag{17.19}$$

Since demand shortage is not allowed, the quantity of reuse components $l$ ($Q_l^{ru}$) has to be greater than or equal to the reuse demand of components $l$ ($D_l^{ru}$). The mathematical function that ensures demand shortage does not occur can be written as follows:

$$Q_l^{ru} \geq D_l^{ru} \tag{17.20}$$

The excess quantity of reuse components $l$ ($Excess_l^{ru}$) is equal to the quantity of reuse components $l$ ($Q_l^{ru}$) subtracted by the reuse demand of components $l$ ($D_l^{ru}$). The mathematical function for the $Excess_l^{ru}$ can be written as follows:

$$Excess_l^{ru} = \sum_l \left( Q_l^{ru} - D_l^{ru} \right) \tag{17.21}$$

The ending inventory quantity of components $l$ ($Q_l^{EInv}$) is equal to the excess quantity of reuse components $l$ ($Excess_l^{ru}$) provided that $Excess_l^{ru}$ does not exceed the inventory capacity limit of components $l$ ($Cap_l^{inv}$). If $Excess_l^{ru}$ is greater than $Cap_l^{inv}$, then $Q_l^{EInv}$ is equaled to $Cap_l^{inv}$ and any excess components beyond the $Cap_l^{inv}$ is disposed of at the end of the period. The mathematical function that ensures that the inventory capacity limits are not violated can be written as follows:

$$Q_l^{EInv} = \begin{array}{cc} Excess_l^{ru}, & Excess_l^{ru} \leq Cap_l^{inv} \\ Cap_l^{inv}, & Excess_l^{ru} \leq Cap_l^{inv} \end{array} \tag{17.22}$$

The reuse disposal quantity of components $l$ ($Q_l^{rudp}$) is equal to the excess quantity of reuse components $l$ ($Excess_l^{ru}$) subtracted by the ending inventory quantity of components $l$ ($Q_l^{Einv}$). The mathematical function for the $Q_l^{rudp}$ can be written as follows:

$$Q_l^{rudp} = \sum_l \left( Excess_l^{ru} - Q_l^{Einv} \right) \tag{17.23}$$

The quantity of destructive disassembled components $k$ in period $l$ ($Q_l^{ddsy}$) is equal to the quantity of disassembled components $k$ in period $l$ ($Q_l^{dsy}$) subtracted by the quantity of nondestructive disassembled components $l$ ($Q_l^{ndsy}$). The mathematical function for the $Q_l^{ddsy}$ can be written as follows:

$$Q_l^{ddsy} = \sum_l \left( Q_l^{dsy} - Q_l^{ndsy} \right) \tag{17.24}$$

The quantity of good destructive disassembled components $l$ ($Q_l^{gddsy}$) is equal to the quantity of destructive disassembled components $l$ ($Q_l^{ddsy}$) multiplied by the recycle percentage of components $l$ ($PCT_l^{rc}$). The mathematical function for the $Q_l^{gddsy}$ can be written as follows:

$$Q_l^{gddsy} = \sum_l Q_l^{ddsy} \cdot PCT_l^{rc} \tag{17.25}$$

The quantity of bad destructive (hazardous) disassembled components $k$ in period $l$ ($Q_l^{bddsy}$) is equal to the quantity of destructive disassembled components $l$ ($Q_l^{ddsy}$) subtracted by the quantity of good destructive disassembled components $l$ ($Q_l^{gddsy}$). The mathematical function for the $Q_l^{bddsy}$ can be written as follows:

$$Q_l^{bddsy} = \sum_l \left( Q_l^{ddsy} - Q_l^{gddsy} \right) \tag{17.26}$$

The quantity of recycle components $k$ in period $l$ ($Q_l^{rc}$) is equal to the quantity of bad nondestructive disassembled components $l$ ($Q_l^{bndsy}$), plus the quantity of good destructive disassembled components $l$ ($Q_l^{gddsy}$), plus the recycle procurement quantity of components $l$ ($Q_l^{rcpr}$). The mathematical function for the $Q_l^{rc}$ can be written as follows:

$$Q_l^{rc} = \sum_l \left( Q_l^{bnddsy} + Q_l^{gddsy} + Q_l^{rcpr} \right) \tag{17.27}$$

Since demand shortage is not allowed, the quantity of recycle components $l$ ($Q_l^{rc}$) has to be greater than or equal to the recycle demand of components

$l$ ($D_l^{rc}$). The mathematical function that ensures demand shortage does not occur can be written as follows:

$$Q_l^{rc} \geq D_l^{rc} \tag{17.28}$$

The quantity of in-plant recycling components $l$ ($Q_l^{irc}$) is equal to the quantity of recycle components $l$ ($Q_l^{rc}$) provided that $Q_l^{rc}$ does not exceed the in-plant recycling capacity limit of components $l$ ($Cap_l^{irc}$). If the $Q_l^{rc}$ is greater than $Cap_l^{irc}$, then $Q_l^{irc}$ is equal to $Cap_l^{irc}$. The mathematical function for the $Q_l^{irc}$ can be written as follows:

$$Q_l^{irc} = \begin{array}{ll} Q_l^{rc}, & Q_l^{rc} \leq Cap_l^{irc} \\ Cap_l^{irc}, & Q_l^{rc} > Cap_l^{rc} \end{array} \tag{17.29}$$

The quantity of out-plant recycling components $l$ ($Q_l^{orc}$) is equal to the quantity of recycle components $l$ ($Q_l^{rc}$) subtracted by the quantity of in-plant recycling components $l$ ($Q_l^{irc}$). The mathematical function for the $Q_l^{orc}$ can be written as follows:

$$Q_l^{orc} = \sum_l \left( Q_l^{rc} - Q_l^{irc} \right) \tag{17.30}$$

The recycle disposal quantity of components $l$ ($Q_l^{rcdp}$) is equal to the quantity of recycle components $k$ in period $l$ ($Q_l^{rc}$) subtracted by the recycle demand of components $l$ ($D_l^{rcdp}$). The mathematical function for the $Q_l^{rcdp}$ can be written as follows:

$$Q_l^{rcdp} = \sum_l \left( Q_l^{rc} - D_l^{rc} \right) \tag{17.31}$$

The total disposal quantity of components $l$ ($Q_l^{dp}$) is equal to the reuse disposal quantity of components $k$ in period $l$ ($Q_l^{rudp}$) plus the recycle disposal quantity of components $l$ ($Q_l^{rcdp}$). The mathematical function for the $Q_l^{dp}$ can be written as follows:

$$Q_l^{dp} = \sum_l \left( Q_l^{rudp} + Q_l^{rcdp} \right) \tag{17.32}$$

The last constraint ensures that the number of EOL product $i$ purchased from supplier $j$ ($Q_{ij}^{EOL}$) does not exceed the capacity limit of purchased EOL product $i$ from supplier $j$ ($Cap_{ij}^{EOL}$). The mathematical function that ensures that the capability limits of the suppliers are not violated can be written as follows:

$$Q_{ij}^{EOL} \; '' \; Cap_{ij}^{EOL} \tag{17.33}$$

$Cap_{ij}^{EOL}$, $Cap_l^{inv}$, $Cap_l^{irc}$, $D_l^{ru}$, $D_l^{rc}$, $Excess_l^{ru}$, $Q_{ij}^{EOL}$, $Q_l^{dsy}$, $Q_l^{nddsy}$, $Q_l^{gnddsy}$, $Q_l^{bnddsy}$, $Q_l^{ru}$, $Q_l^{ddsy}$, $Q_l^{gddsy}$, $Q_l^{bddsy}$, $Q_l^{rc}$, $Q_l^{irc}$, $Q_l^{orc}$, $Q_l^{pr}$, $Q_l^{rupr}$, $Q_l^{rcpr}$, $Q_l^{Sinv}$, $Q_l^{Einv}$, $Q_l^{dp}$, $Q_l^{rudp}$ and $Q_l^{rcdp}$ must be integers, and all variables are nonnegative.

### 17.2.3 Nonlinear Programming Model

The NLP model associated with the problem can be written as follows:

$$Max\, Z\,(\text{Profit}) = R_{RU} + R_{RC} - \sum_{j}((1 - DR_j)\cdot C_{PEOL_j})$$

$$- C_{DSY} - C_{INV} - C_{PC} - C_{RC} - C_{DIS}$$

$$\text{Solve for } \left(Q_{ij}^{EOL}, Q_l^{dsy}, Q_l^{nddsy}, Q_l^{ddsy}, Q_l^{rc}, Q_l^{rupr}, Q_l^{rcpr}, Q_l^{Einv}, \text{ and } Q_l^{dp}\right) \tag{17.34}$$

where revenue and cost functions are defined in Equation (17.1) through Equation (17.14), and the constrains are defined in Equation (17.15) through Equation (17.33).

### 17.2.4 Example

The problem considered in this section involves four suppliers. Each supplier offers three different types of products consisting of eight different components. Component characteristics are presented in Table 17.1. Prices and conditions of products differ from one supplier to the other. Purchase price

**TABLE 17.1**

Component Characteristics

| Component | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| Reuse percentage | 75% | 90% | 70% | 80% | 60% | 85% | 80% | 70% |
| Reuse selling price | 12 | 13 | 15 | 14 | 18 | 15 | 14 | 15 |
| Reuse demand | 500 | 450 | 400 | 600 | 300 | 500 | 400 | 450 |
| Recycle percentage | 95% | 92% | 98% | 90% | 99% | 90% | 95% | 96% |
| Recycle selling price | \$7 | \$8 | \$6 | \$9 | \$8 | \$7 | \$7 | \$7 |
| Recycle demand | 100 | 200 | 120 | 180 | 225 | 200 | 100 | 75 |
| Procurement cost | 9 | 11 | 14 | 10 | 14 | 13 | 10 | 12 |
| Disposal cost | 0.70 | 0.60 | 0.45 | 0.50 | 0.70 | 0.65 | 0.55 | 0.60 |
| Bad destructive disposal cost | \$2.5 | \$2.5 | \$2.5 | \$2.5 | \$2.5 | \$2.5 | \$2.5 | \$2.5 |
| Holding cost | \$1.00 | \$1.25 | \$1.45 | \$1.15 | \$1.00 | \$1.55 | \$1.45 | \$1.25 |
| Destructive disassembly cost | \$1.50 | \$1.25 | \$1.30 | \$1.60 | \$1.45 | \$1.45 | \$1.25 | \$1.50 |
| Nondestructive disassembly cost | \$3.00 | \$2.50 | \$2.50 | \$2.40 | \$2.80 | \$2.70 | \$2.60 | \$3.00 |
| In-plant recycle cost | \$1.2 | \$1.2 | \$1.2 | \$1.2 | \$1.2 | \$1.2 | \$1.2 | \$1.2 |
| Out-plant recycle cost | \$2.0 | \$2.0 | \$2.0 | \$2.0 | \$2.0 | \$2.0 | \$2.0 | \$2.0 |
| In-plant capacity | 200 | 200 | 200 | 200 | 200 | 200 | 200 | 200 |
| Inventory capacity | 400 | 400 | 400 | 400 | 400 | 400 | 400 | 400 |
| Starting inventory | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**TABLE 17.2**

Purchase Price and Capacity of Suppliers for Each Product Type

| | | Products | | |
|---|---|---|---|---|
| **Supplier** | **Price and Capacity** | **1** | **2** | **3** |
| Supplier 1 | Purchase price | $30 | $22 | $27 |
| | Capacity | 100 | 150 | 45 |
| Supplier 2 | Purchase price | $30 | $24 | $27 |
| | Capacity | 150 | 50 | 100 |
| Supplier 3 | Purchase price | $29 | $21 | $26 |
| | Capacity | 150 | 140 | 75 |
| Supplier 4 | Purchase price | $27 | $21 | $25 |
| | Capacity | 150 | 200 | 75 |

and capacity of suppliers for each product type can be seen in Table 17.2. Each supplier offers discount schedules based on the total dollar amount purchased. Tables 17.3 through 17.6 present the discount schedules offered by suppliers 1 through 4, respectively.

One-to-one heuristic (Inderfurth and Langella, 2006) is used to calculate the component yields from each product type for every supplier (see Section 20.6.2). Yield information for suppliers is as follows: $yld_1^+ = 0.85$, $yld_1^- = 0.65$ for supplier 1, $yld_2^+ = 0.90$, $\mathrm{yld}_2^{--} = 0.70$ for supplier 2, $\mathrm{yld}_3^+ = 0.80$, $\mathrm{yld}_3^- = 0.50$ for supplier 3, $\mathrm{yld}_4^+ = 0.75$, $\mathrm{yld}_4^{--} = 0.65$ for supplier 4. The calculated component yields are presented in Table 17.7.

**TABLE 17.3**

Discount Rates for Supplier 1

| **Total Purchase in Dollars** | **Discount Rate** |
|---|---|
| $0 < TP < 2000$ | 0.0% |
| $2000 < TP < 3500$ | 4.0% |
| $3500 < TP < 5000$ | 6.0% |
| $TP \geq 5000$ | 9.0% |

**TABLE 17.4**

Discount Rates for Supplier 2

| **Total Purchase in Dollars** | **Discount Rate** |
|---|---|
| $0 < TP < 2000$ | 0.0% |
| $2000 < TP < 3500$ | 3.0% |
| $3500 < TP < 5000$ | 5.0% |
| $TP \geq 5000$ | 8.0% |

**TABLE 17.5**

Discount Rates for Supplier 3

| Total Purchase in Dollars | Discount Rate |
|---|---|
| 0 < TP < 2000 | 0.0% |
| 2000 < TP < 3500 | 2.5% |
| 3500 < TP < 5000 | 6.0% |
| TP ≥ 5000 | 7.5% |

**TABLE 17.6**

Discount Rates for Supplier 4

| Total Purchase in Dollars | Discount Rate |
|---|---|
| 0 < TP < 2000 | 0.0% |
| 2000 < TP < 3500 | 2.0% |
| 3500 < TP < 5000 | 4.0% |
| TP ≥ 5000 | 7.0% |

**TABLE 17.7**

Component Yields for Suppliers

| | Supplier 1 | | | Supplier 2 | | | Supplier 3 | | | Supplier 4 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Product | | | Product | | | Product | | | Product | | |
| Component | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| C1 | 0.83 | 0 | 0.82 | 0.87 | 0 | 0.86 | 0.80 | 0 | 0.78 | 0.74 | 0 | 0.74 |
| C2 | 0.83 | 0.80 | 0.82 | 0.87 | 0.85 | 0.86 | 0.80 | 0.76 | 0.78 | 0.74 | 0.73 | 0.73 |
| C3 | 0.83 | 0 | 0.82 | 0.87 | 0 | 0.86 | 0.80 | 0 | 0.78 | 0.74 | 0 | 0.73 |
| C4 | 0 | 0.80 | 0.82 | 0 | 0.85 | 0.86 | 0 | 0.76 | 0.78 | 0 | 0.73 | 0.73 |
| C5 | 0 | 0.80 | 0.82 | 0 | 0.85 | 0.86 | 0 | 0.76 | 0.78 | 0 | 0.73 | 0.73 |
| C6 | 0.83 | 0.80 | 0.82 | 0.87 | 0.85 | 0.86 | 0.80 | 0.76 | 0.78 | 0.74 | 0.73 | 0.73 |
| C7 | 0.83 | 0.80 | 0 | 0.87 | 0.85 | 0 | 0.80 | 0.76 | 0 | 0.74 | 0.73 | 0 |
| C8 | 0.83 | 0.80 | 0 | 0.87 | 0.85 | 0 | 0.80 | 0.76 | 0 | 0.74 | 0.73 | 0 |

**TABLE 17.8**

Summary of Results for Suppliers

| | Purchase Quantity | | | | | |
|---|---|---|---|---|---|---|
| | Product | | | | | |
| Supplier | 1 | 2 | 3 | Total Purchase | Discount Rate | Total Purchase After Discount |
| 1 | 0 | 150 | 24 | 3948 | 6.00% | $3711.12 |
| 2 | 90 | 50 | 100 | 6600 | 8.00% | $6072.00 |
| 3 | 29 | 140 | 75 | 4890 | 6.00% | $4596.60 |
| 4 | 0 | 46 | 3 | 1041 | 0.00% | $1041.00 |

**TABLE 17.9**

Summary of Results for Components

| | | Outside Procurement | | Disposal Quantity | | |
|---|---|---|---|---|---|---|
| **Component** | **Ending Inventory** | **Reuse Procurement** | **Recycle Procurement** | **Excess Reuse** | **Excess Recycle** | **Contaminated Quantity** |
| C1 | 0 | 317 | 0 | 0 | 6 | 2 |
| C2 | 43 | 1 | 25 | 43 | 0 | 11 |
| C3 | 0 | 229 | 0 | 0 | 0 | 1 |
| C4 | 0 | 225 | 0 | 0 | 21 | 12 |
| C5 | 0 | 19 | 0 | 0 | 81 | 1 |
| C6 | 0 | 35 | 0 | 0 | 0 | 13 |
| C7 | 0 | 95 | 0 | 0 | 67 | 5 |
| C8 | 0 | 184 | 0 | 0 | 131 | 4 |

The nonlinear programming model was solved using LINGO 11. Total profit was found to be $20,559.23 Total purchase quantity of EOL products from each supplier, total dollar purchase from each supplier, and discount rate given by each supplier can be seen in Table 17.8. Table 17.9 gives the quantities of procured and disposed components, together with the ending inventory for each component.

## 17.3 Second Model (Fuzzy Programming)

In this approach, Taguchi Loss Functions and AHP are used for the qualitative evaluation of suppliers, while the order quantities are determined through the use of fuzzy programming. In the following subsections, the implementation details of this methodology are discussed by presenting a numerical example.

### 17.3.1 Qualitative Evaluation (Ranking) of Suppliers

For the qualitative evaluation of suppliers, the three-step methodology presented in Section 16.2 can be employed to rank order the suppliers.

### 17.3.2 Determination of Order Quantities with Fuzzy Mathematical Programming

Much of the input information used in the supplier selection process is uncertain. While selecting a supplier, imprecise terms like "*approximately more than*" or "*approximately less than*" or "*somewhere between,*" etc., are commonly used to express the values of many criteria. Deterministic models cannot capture such vagueness. Therefore, such problems need to be modeled as a fuzzy model, in which the overall aspiration level is maximized rather than strictly satisfying the constraints (Kumar et al., 2006). Fuzzy mathematical programming has the capability to handle multiobjective problems and vagueness of the linguistic type (Zimmermann, 1978). Using Zimmermann (1978), the multiobjective programming problem with fuzzy goals and constraints can be transformed into a crisp linear programming formulation that can be solved using conventional optimization software. The multiobjective integer programming supplier selection problem (MIP-SSP) for three objectives (namely, total loss of profit [TLP], total cost of purchase [TCP], and percentage rejections [PR]) and the relevant system constraints is given next:

$$\text{Goal 1: Minimize TLP: } \sum_{j=1}^{s} Loss_j \cdot Q_j = TLP \tag{17.35}$$

$$\text{Goal 2: Minimize TCP: } \sum_{j=1}^{s} c_j \cdot Q_j = TCP \tag{17.36}$$

$$\text{Goal 3: Minimize PR: } \sum_{j=1}^{s} p_j \cdot Q_j = PR \tag{17.37}$$

$$\text{Capacity constraint: } Q_j \;{''}\; r_j \tag{17.38}$$

$$\text{Demand constraint: } \sum_{j} Q_j = D \tag{17.39}$$

$$\text{Budget allocation constraint: } \sum_{j} c_j \cdot Q_j \le B_j \tag{17.40}$$

$$\text{Nonnegativity constraint: } Q_j \ge 0 \tag{17.41}$$

where

$B_j$: Budget allocated for supplier $j$
$c_j$: Unit purchasing cost of product from supplier $j$
$D$: Demand for the product
$j$: Supplier index, $j = 1, 2, \ldots, s$
$Loss_j$: Total loss of supplier $j$ for all the critical evaluation criteria
$r_j$: Capacity of supplier $j$
$p_j$: Probability of breakage of products purchased from supplier $j$
$Q_j$: Decision variable representing the purchasing quantity from supplier $j$
s: Number of alternate suppliers available

For solving the fuzzy multiobjective integer programming supplier selection problem (MIP-SSP), a linear membership function is considered for all fuzzy parameters. A linear membership function has a continuously increasing or decreasing value over the range of the parameter. It is defined by the lower and upper values of the acceptability for that parameter.

A fuzzy objective $\tilde{Z} \in X$ is a fuzzy subset of $X$ characterized by its membership function $_z(x): x \to [0,1]$. The linear membership function for the fuzzy objectives is given by

$$_{z_j}(x) = \begin{array}{cl} 1 & \mathit{if}\ Z_j(x) \le Z_j^{\min}, \\ Z_j^{\max} - Z_j(x)\ \ /\ \ Z_j^{\max} - Z_j(x) & \mathit{if}\ Z_j^{\min} \le Z_j(x) \le Z_j^{\max} \\ 0 & \mathit{if}\ Z_j^{\max} - Z_j(x) \end{array} \tag{17.42}$$

where $Z_j^{\min}$ is min$_j$ $Z_j(x^*)$, $Z_j^{\max}$ is max$_j$ $Z_j(x^*)$, and $x^*$ is optimum solution.

A fuzzy constraint $C \in X$ is a fuzzy subset of $X$ characterized by its membership function. $_c(x): x \to [0,1]$. The linear membership function for the fuzzy constraints is given by

$$_{z_{k_j}}(x) = \begin{array}{cl} 1 & \mathit{if}\ g_k(x) \le b_k, \\ [1 - \{g_k(x) - b_k\} / d_k] & \mathit{if}\ b_k \le g_k(x) \le b_k + d_k \\ 0 & \mathit{if}\ b_k + d_k \le g_k(x) \end{array} \tag{17.43}$$

where $d_k$ is the tolerance interval.

The fuzzy programming model for $J$ objectives and $K$ constraints is transformed into the following *crisp* formulation:

Maximize $\lambda$
Subject to

$$\begin{array}{ll} \lambda \cdot \left(Z_j^{\max} - Z_j^{\min}\right) + Z_j(x) \le Z_j^{\max} & \text{for all } j,\ j = 1,2,\ldots,J, \\ \lambda \cdot (d_x) + g_k(x) \le b_k + d_k & \text{for all } k,\ k = 1,2,\ldots,K, \\ Ax \le b & \text{for all deterministic constraints} \\ x \ge 0 \quad \text{and} \quad \text{integer}, & \\ 0 \le \lambda \le 1 & \end{array} \tag{17.44}$$

where $\lambda$ is the overall degree of satisfaction.

Zimmermann(1978) suggested the use of individual optima as lower bound ($Z_j^{\min}$) and upper bound ($Z_j^{\max}$) of the optimal values for each objective.

The lower bound ($Z_j^{\min}$) and upper bounds ($Z_j^{\max}$) of the optimal values are obtained by solving the (MIP-SSP) as a linear programming problem using one objective each time, and ignoring all the others:

$$
\begin{array}{ll}
\text{Minimize/Maximize} \quad Z_j(x) & \text{for all } j,\ j = 1,2,\ldots,J \\
\text{Subject to} & \\
g_k(x) \le b_k + d_k & \text{for all } k,\ k = 1,2,\ldots,K \\
Ax \le b & \text{for all deterministic constraints} \\
x \ge 0 \quad \text{and} \quad \text{integer} &
\end{array}
\tag{17.45}
$$

A complete solution of the (MIP-SSP) problem is obtained through the following steps:

*Step 1*: Transform the supplier selection problem into the (MIP-SSP) form.

*Step 2*: Select the first objective and solve it as a linear programming problem with the system constraints; maximizing the objective gives the upper bound and minimizing the objective gives the lower bound of the optimal values of the objective.

*Step 3*: Use these values as the lower and upper bound of the optimal values for the *crisp* formulation of the problem.

*Step 4*: Formulate and solve the equivalent *crisp* formulation of the fuzzy optimization problem maximizing the overall satisfaction level.

### 17.3.3 Numerical Example

We consider a problem involving four suppliers and four criteria (viz., quality, on-time delivery, proximity, and cultural and strategic issues). First, the three-step AHP–Taguchi loss functions–based methodology is employed for the qualitative evaluation of the suppliers (see Section 16.2). Then order quantities from each supplier are determined using fuzzy mathematical programming.

#### *17.3.3.1 Three-Step AHP–Taguchi Loss Functions–Based Methodology*

Step 1: The comparative importance values and the normalized eigenvalue vector of the criteria are given in Table 17.10. In this table, the relative impacts given by the decision maker to the criteria are represented with the normalized eigenvalue vector. The pairwise comparisons shown in Table 17.10 are consistent since CR value is equal to 0.030.

**TABLE 17.10**

Comparative Importance Values of Criteria

| Criteria | Quality | On-Time Delivery | Proximity | Cultural and Strategic Issues | Normalized Eigenvector |
|---|---|---|---|---|---|
| Quality | 1 | 2 | 6 | 1 | 0.360809 |
| On-time delivery | 0.5 | 1 | 3 | 0.25 | 0.154614 |
| Proximity | 0.166 | 0.333 | 1 | 0.2 | 0.063574 |
| Cultural and strategic issues | 1 | 4 | 5 | 1 | 0.421003 |

*Step 2:* Various specifications for the criteria are given in Table 17.11. According to this table, we can illustrate the calculation of Taguchi losses for each criterion as follows:

- *Quality:* The target defect rate/breakage probability is zero, at which there is no loss to the manufacturer, and the upper specification limit for the defect rate/breakage probability is 20%, at which there is a 100% loss to the manufacturer.
- *On-time delivery:* Loss will occur if the products are delivered late or they are delivered before the scheduled date. The specification limit is 5 days for early and delayed delivery. According to this specification, 100% loss will occur if the delivery is done with a 5 days' delay or if the delivery is done 5 days earlier.
- *Proximity:* The closest supplier has a zero loss. Since the specification limit is up to 40% of the closest supplier, the manufacturer will incur the 100% loss when a supplier's distance reaches to this specification limit.
- *Cultural and strategic issues:* Cultural and strategic issues are hard to quantify for the calculation of Taguchi losses. Monczka and Trecha (1998) proposed a service factor rating (SFR) that includes performance factors difficult to quantify but are decisive in the supplier selection process. In practice, experts rate these performance factors. For a given supplier, these ratings on all factors are summed and averaged to obtain a total service rating. The supplier's service factor percentage is obtained by dividing the total service rating by the total

**TABLE 17.11**

Various Specifications for Decision Criteria

| Criteria | Target Value | Range | Specification Limit |
|---|---|---|---|
| Quality | 0% | 0%–20% | 20% |
| On-time delivery | 0 | 5–0–5 | 5 days earlier, 5 day's delay |
| Proximity | Closest | 0%–30% | 30% higher |
| Cultural and strategic issues | 100% | 100%–40% | 40% |

**TABLE 17.12**

Service Factor Ratings of Suppliers for Cultural and Strategic Issues

| Supplier | Economic Performance and Financial Stability | Environmental Image | Cooperation Level and Info Exchange | Flexibility | Average | Average/10 |
|---|---|---|---|---|---|---|
| 1 | 5 | 5 | 7 | 6 | 5.75 | 57.5% |
| 2 | 6 | 7 | 5 | 6 | 6 | 60.0% |
| 3 | 7 | 5 | 4 | 4 | 5 | 50.0% |
| 4 | 6 | 4 | 7 | 8 | 6.25 | 62.5% |

number of points possible. Table 17.12 shows the service factor ratings for the subcriteria considered under the cultural and strategic issues criteria for the three suppliers. The ratings are given on a scale of 1–10, the level of importance being directly proportional to the rating.

Computing the value of loss coefficient, *k*, using appropriate Equations (2.1), (2.2) or (2.3) gives a value of 2500, 1111.11, 16, and 4 for quality, proximity, cultural, and strategic issues and on-time delivery, respectively.

The characteristic and relative values for each supplier are summarized in Table 17.13. Table 17.14 shows the Taguchi losses for each criterion calculated from the appropriate loss functions for the individual suppliers.

**TABLE 17.13**

Characteristic and Relative Values of Criteria for Each Supplier

| | Quality | | On-Time Delivery | | Proximity | | Cultural and Strategic Issues | |
|---|---|---|---|---|---|---|---|---|
| Supplier | Value | Relative Value | Value | Relative Value | Value | Relative Value | Value | Relative Value |
| 1 | 10% | 10% | +4 | +4 | 8 | 100% | 57.5% | 57.5% |
| 2 | 15% | 15% | +2 | +2 | 6 | 50% | 60.0% | 60.0% |
| 3 | 10% | 10% | –1 | –1 | 4 | 0 | 50.0% | 50.0% |
| 4 | 20% | 20% | +3 | +3 | 5 | 25% | 62.5% | 62.5% |

**TABLE 17.14**

Characteristic Taguchi Losses for Each Supplier

| Supplier | Quality | On-time Delivery | Proximity | Cultural and Strategic Issues |
|---|---|---|---|---|
| 1 | 25 | 64 | 1111.1 | 48.39 |
| 2 | 56.25 | 16 | 277.78 | 44.44 |
| 3 | 25 | 4 | 0 | 64 |
| 4 | 100 | 36 | 69.44 | 40.96 |

**TABLE 17.15**

Weighted Taguchi Losses

| Supplier | Weighted Taguchi Loss | Normalized Taguchi Loss |
|---|---|---|
| 1 | 109.92 | 0.446684 |
| 2 | 59.14 | 0.240328 |
| 3 | 13.71 | 0.055714 |
| 4 | 63.31 | 0.257274 |

*Step 3:* Weighted Taguchi loss value for each supplier is calculated using the Equation (16.1). Weighted and normalized weighted Taguchi loss values are presented in Table 17.15. According to this table, the best supplier is supplier 3.

#### *17.3.3.2 Fuzzy Mathematical Programming*

Supplier profiles considered in the example can be seen in Table 17.16. Expressions given in Equations (17.42) and (17.43) were used to determine the values of the objectives *TLP, TCP, PR,* and fuzzy constraints. Uncertainty levels of all fuzzy parameters (capacities and budget allocations) are taken as the 20% of the deterministic model. Net demand is considered to be a deterministic constraint, and a net demand value of 2000 is used in this example. The lowest and highest aspiration levels of the membership functions are presented in Table 17.17. In this table, $Z_j^{\min}$ and $Z_j^{\max}$ are obtained by solving Equation (17.45).

Based on the Equation (17.44), the *crisp* formulation for the illustrative example is as follows:

*Maximize* $\lambda$

*Subject to*

$$386.9568\,\lambda + 0.446684Q1 + 0.240328Q2 + 0.055714Q3 + 0.257274Q4 <= 673.6524$$

$$968\,\lambda + 1.2Q1 + 2.2Q2 + 1.8Q3 + 2Q4 <= 4080$$

$$34.8\,\lambda + 0.05Q1 + 0.04Q2 + 0.03Q3 + 0.02Q4 <= 82.8$$

$$Q1 + Q2 + Q3 + Q4 = 2000$$

$$140\,\lambda + Q1 <= 840$$

**TABLE 17.16**

Profile of Each Supplier

| Supplier | Unit Cost | Breakage Probability | Capacity | Budget Allocation |
|---|---|---|---|---|
| 1 | 1.2 | 0.05 | 700 | 2000 |
| 2 | 2.2 | 0.04 | 500 | 1500 |
| 3 | 1.8 | 0.03 | 900 | 2500 |
| 4 | 2 | 0.02 | 1000 | 3000 |

**TABLE 17.17**

Limiting Values in Membership Function for Fuzzy Objectives and Fuzzy Constraints

| | $\mu = 1$ | $\mu = 0$ |
|---|---|---|
| Total loss of purchase | 286.6956 | 673.6524 |
| Total cost of purchase | 3112 | 4080 |
| Percentage rejections | 48 | 82.8 |
| *Capacity Constraints* | | |
| Supplier 1 | 700 | 840 |
| Supplier 2 | 500 | 600 |
| Supplier 3 | 900 | 1080 |
| Supplier 4 | 1000 | 1200 |
| *Budget Allocations* | | |
| Supplier 1 | 2000 | 2400 |
| Supplier 2 | 1500 | 1800 |
| Supplier 3 | 2500 | 3000 |
| Supplier 4 | 3000 | 3600 |

$100\ \lambda + Q2 <= 600$

$180\ \lambda + Q3 <= 1080$

$200\ \lambda + Q4 <= 1200$

$400\ \lambda + 1.2Q1 <= 2400$

$300\ \lambda + 2.2Q2 <= 1800$

$500\ \lambda + 1.8Q3 <= 3000$

$600\ \lambda + 2Q4 <= 3600$

$Q1, Q2, Q3 \geq 0$ and integers

The above model is solved using LINGO 11 and the maximum degree of overall satisfaction achieved is $\lambda_{max} = 0.6155172$ for the supplier quantities: $Q1 = 442$, $Q2 = 0$, $Q3 = 812$, and $Q4 = 746$. This solution yields a net *TLP* =672.78, *TCP* =4079.82, and *PR* =82.8.

## 17.4 Other Models

Massoud and Gupta (2009) employ dynamic programming to determine the optimal number of EOL products to be collected in every period from each supplier to fulfill the demand of components based on the maximization of total profit.

Some multicriteria decision-making models were also developed to solve optimal supplier portfolio problem. Massoud and Gupta, 2010b use preemptive goal programming to determine the optimal number of take-back EOL products in every period from each supplier in order to satisfy the demand of components and materials while trying to achieve the aspiration levels of multiple goals (viz., profit, procurement cost, purchase cost, disposal cost, disassembly cost, inventory cost, recycling cost, nondestructive cost, destructive cost). Another multicriteria approach is developed by Massoud and Gupta (2010a) based on linear physical programming. They define profit as Class 2S while cost-related goals (procurement cost, purchase cost, and disposal cost) are defined as Class 1S.

## 17.5 Conclusions

We presented two models in this chapter for determining the optimal supplier portfolio. The first model used nonlinear programming while the second model integrated Taguchi loss functions, AHP, and fuzzy programming. Recent literature was reviewed in the previous section.

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# 18

# *Selection of Third-Party Reverse Logistics Providers*

## 18.1 The Issue

Outsourcing of reverse logistics (RL) operations to third-party logistics providers (3PLs) is a practice adopted by many firms due to differences between the reverse and forward flows in terms of the cost and complexity of transportation, storage, and/or handling operations (Meade and Sarkis, 2002; Efendigil et al., 2008). In order to assist companies in selecting the best 3PL, researchers have developed various multicriteria decision-making (MCDM) methodologies. In this chapter, we first present the application of a popular MCDM technique, AHP, to an illustrative 3PL selection problem. Then, an overview of the criteria and techniques employed in the literature is presented.

## 18.2 An AHP Model

In this section, an analytic hierarchy process is used to determine the most suitable 3PL from a set of candidate 3PLs. Section 18.2.1 presents the three-level hierarchy structure of AHP while a numerical example is presented in Section 18.2.2.

### 18.2.1 AHP Hierarchy

The goal, that is, determination of the most suitable 3PL, is the first level in the hierarchy. Candidate 3PLs are considered in the last level. Between these two levels, the criteria used to evaluate the candidates are placed. The three-level AHP hierarchy can be seen in Figure 18.1. Table 18.1 provides the abbreviations and explanations for the evaluation criteria.

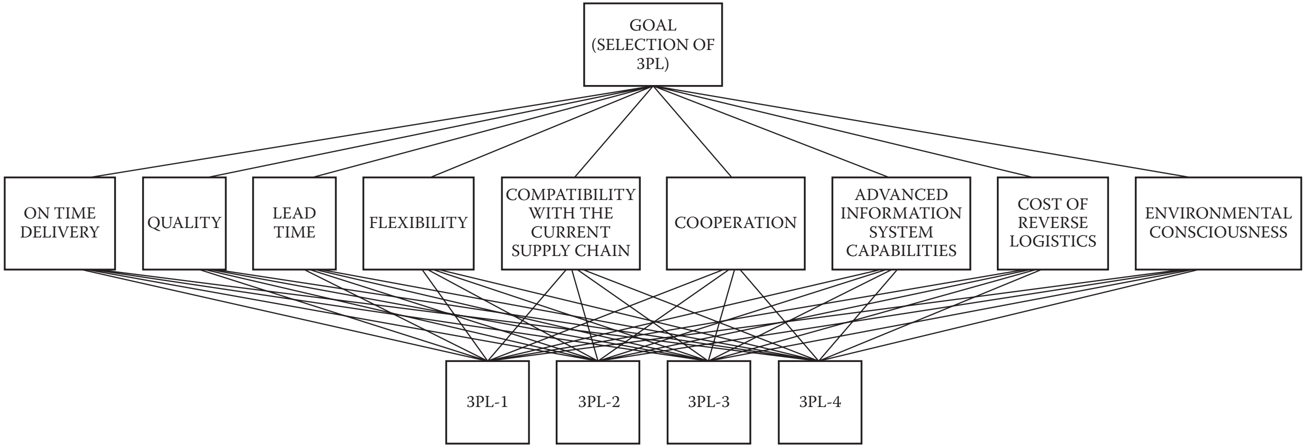

**FIGURE 18.1**
Three-level AHP structure.

**TABLE 18.1**

Explanations for 3PL Selection Criteria

| Criterion | Abbreviation | Explanation |
|---|---|---|
| On-time delivery | OTD | Ability of meeting delivery schedules. |
| Quality | Q | Conformance of products to specifications, effective inspection methods, and quality consciousness. |
| Lead time | LT | Ability of completing an order in a short period of time. |
| Flexibility | F | Ability of satisfying customer needs with respect to timing, size, and location of an order. |
| Compatibility with the current supply chain | CCSC | Integration level of 3PL's E-commerce, B2C, B2B, ERP systems with the company. |
| Cooperation | C | Close relationship between the 3PL and the company and the willingness of the 3PL to work with the company. |
| Advanced information system capabilities | AIS | Ability of providing advanced information applications like online tracking. |
| Cost of reverse logistics | CRL | All costs related with RL including transportation cost, storage cost, inventory cost, packaging cost, etc. |
| Environmental consciousness | EC | Environmentally conscious business practices implemented by the 3PL, such as ISO-14000 certification. |

### 18.2.2 Numerical Example

Consider the following example: pairwise comparisons among the criteria are presented in Table 18.2 together with the normalized eigenvector. This vector shows the importance of each criterion based on decision-makers' preferences. Tables 18.3 through 18.11 show pairwise comparisons of the

**TABLE 18.2**

Comparative Importance Values of Criteria

| Criterion | OTD | Q | LT | F | CCSC | C | AISC | CRL | EC | Normalized Eigenvector |
|---|---|---|---|---|---|---|---|---|---|---|
| OTD | 1 | ⅓ | 1 | 1 | 3 | 2 | 1 | 2 | 4 | 0.137446 |
| Q | 3 | 1 | 2 | 2 | 2 | 2 | 3 | 2 | 3 | 0.208226 |
| LT | 1 | ½ | 1 | 2 | 2 | 2 | 2 | 3 | 3 | 0.158241 |
| F | 1 | ½ | ½ | 1 | ½ | 1 | 2 | ½ | 3 | 0.088670 |
| CCSC | ⅓ | ½ | ½ | 2 | 1 | ⅓ | 2 | ⅓ | 2 | 0.080487 |
| C | ½ | ½ | ½ | 1 | 3 | 1 | ½ | ½ | 2 | 0.086296 |
| AISC | 1 | ⅓ | ½ | ½ | ½ | 2 | 1 | ½ | 2 | 0.077495 |
| CRL | ½ | ½ | ⅓ | 2 | 3 | 2 | 2 | 1 | 3 | 0.123558 |
| EC | ¼ | ⅓ | ⅓ | ⅓ | ½ | ½ | ½ | ⅓ | 1 | 0.039581 |

*Note:* CR = 0.0713.

**TABLE 18.3**

Comparative Importance Values of 3PLs with Respect to "On Time Delivery" Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | 3 | 2 | 2 | 0.415730 |
| 3PL-2 | ⅓ | 1 | 1 | ½ | 0.149642 |
| 3PL-3 | ½ | 1 | 1 | 2 | 0.237249 |
| 3PL-4 | ½ | 2 | ½ | 1 | 0.197379 |

*Note:* CR = 0.0640.

**TABLE 18.4**

Comparative Importance Values of 3PLs with Respect to "Quality" Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | 2 | 2 | 2 | 0.388011 |
| 3PL-2 | ½ | 1 | 1 | ⅓ | 0.151194 |
| 3PL-3 | ½ | 1 | 1 | 1 | 0.194005 |
| 3PL-4 | ½ | 3 | 1 | 1 | 0.266790 |

*Note:* CR = 0.0579.

**TABLE 18.5**

Comparative Importance Values of 3PLs with Respect to "Lead Time" Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | ½ | 2 | 3 | 0.279840 |
| 3PL-2 | 2 | 1 | 4 | 2 | 0.443410 |
| 3PL-3 | ½ | ¼ | 1 | 2 | 0.154454 |
| 3PL-4 | ⅓ | ½ | ½ | 1 | 0.122296 |

*Note:* CR = 0.0775.

**TABLE 18.6**

Comparative Importance Values of 3PLs with Respect to "Flexibility" Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | ½ | 1 | ¼ | 0.136567 |
| 3PL-2 | 2 | 1 | 1 | ⅓ | 0.200803 |
| 3PL-3 | 1 | 1 | 1 | 1 | 0.235708 |
| 3PL-4 | 4 | 3 | 1 | 1 | 0.426922 |

*Note:* CR = 0.0908.

**TABLE 18.7**

Comparative Importance Values of 3PLs with Respect to "Compatibility with the Current Supply Chain" Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | 1 | 1 | ½ | 0.178725 |
| 3PL-2 | 1 | 1 | ¼ | ⅕ | 0.103171 |
| 3PL-3 | 1 | 4 | 1 | ⅓ | 0.232675 |
| 3PL-4 | 2 | 5 | 3 | 1 | 0.485428 |

*Note:* CR = 0.0888.

**TABLE 18.8**

Comparative Importance Values of 3PLs with Respect to "Cooperation" Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | 2 | 4 | 6 | 0.505663 |
| 3PL-2 | ½ | 1 | 2 | 5 | 0.294081 |
| 3PL-3 | ¼ | ½ | 1 | 1 | 0.116103 |
| 3PL-4 | ⅙ | ⅕ | 1 | 1 | 0.084152 |

*Note:* CR = 0.0300.

**TABLE 18.9**

Comparative Importance Values of 3PLs with Respect to Advanced Information System Capabilities Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | 1 | 4 | 4 | 0.401964 |
| 3PL-2 | 1 | 1 | 3 | 5 | 0.389964 |
| 3PL-3 | ¼ | ⅓ | 1 | 1 | 0.128280 |
| 3PL-4 | ¼ | ⅕ | 1 | 1 | 0.079792 |

*Note:* CR = 0.0152.

candidate 3PLs with respect to the evaluation criteria, OTD, Q, LT, F, CCSC, C, AISC, CRL, and EC, respectively. It must be noted that each pairwise comparison has a consistency ratio CR of less than or equal to 0.10. CR values can be seen under each table. As an example, CR value for Table 18.7 can be calculated as follows:

$$CR = \frac{(\lambda_{\max} - n)}{(n-1)\cdot R} = \frac{(4.24 - 4)}{(4-1)\cdot 0.90} = 0.0888$$

**TABLE 18.10**

Comparative Importance Values of 3PLs with Respect to Cost of Reverse Logistics Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | 3 | 4 | 2 | 0.485543 |
| 3PL-2 | ⅓ | 1 | 2 | 2 | 0.232664 |
| 3PL-3 | ¼ | ½ | 1 | 1 | 0.126158 |
| 3PL-4 | ½ | ½ | 1 | 1 | 0.155636 |

*Note:* CR = 0.0442.

**TABLE 18.11**

Comparative Importance Values of 3PLs with Respect to Environmental Consciousness Criterion

| | 3PL-1 | 3PL-2 | 3PL-3 | 3PL-4 | Normalized Eigenvector |
|---|---|---|---|---|---|
| 3PL-1 | 1 | 1 | 3 | 3 | 0.369702 |
| 3PL-2 | 1 | 1 | 2 | 5 | 0.360296 |
| 3PL-3 | ⅓ | ½ | 1 | 4 | 0.193060 |
| 3PL-4 | ⅓ | ⅕ | ¼ | 1 | 0.076942 |

*Note:* CR = 0.0620.

where $\lambda_{\max}$ is the principal eigenvalue of the pairwise comparisons matrix, $n$, is the number of rows (or columns) in the matrix, and $R$ is the random index for each $n$ value that is greater than or equal to 1 (see Section 2.3).

We obtain the following normalized ranks for 3PLs by multiplying the aggregate matrix in Table 18.12 with the normalized eigenvector presented in Table 18.2: $\text{Rank}_{3PL\text{-}1}$: 0.358124, $\text{Rank}_{3PL\text{-}2}$: 0.246932, $\text{Rank}_{3PL\text{-}3}$: 0.180264, $\text{Rank}_{3PL\text{-}4}$: 0.214680.

**TABLE 18.12**

Aggregate of Ratings of 3PLs

| | OTD | Q | LT | F | CCSC | C | AISC | CRL | EC |
|---|---|---|---|---|---|---|---|---|---|
| 3PL-1 | 0.415730 | 0.388011 | 0.279840 | 0.136567 | 0.178725 | 0.505663 | 0.401964 | 0.485543 | 0.369702 |
| 3PL-2 | 0.149642 | 0.151194 | 0.443410 | 0.200803 | 0.103171 | 0.294081 | 0.389964 | 0.232664 | 0.360296 |
| 3PL-3 | 0.237249 | 0.194005 | 0.154454 | 0.235708 | 0.232675 | 0.116103 | 0.128280 | 0.126158 | 0.193060 |
| 3PL-4 | 0.197379 | 0.266790 | 0.122296 | 0.426922 | 0.485428 | 0.084152 | 0.079792 | 0.155636 | 0.076942 |

## 18.3 Other Models

There are many multicriteria decision-making methodologies developed for the selection of 3PLs. ANP is used by Meade and Sarkis (2002) to develop a conceptual model for selecting and evaluating 3PLs. Activity Based Costing (ABC), balanced scorecard, AHP, and QFD are used to select between two competing 3PLs in Presley et al. (2007). A holistic approach integrating neural networks and fuzzy logic is proposed by Efendigil et al. (2008) for selecting a 3PL in the presence of vagueness. In Tsai and Hung (2009), treatment supplier selection problem of an electronic equipment manufacturer is solved by employing preemptive GP with environmental goals, ABC goals, and supply chain goals. AHP is used to calculate the performance weights of suppliers. A TOPSIS-based methodology is proposed by Pochampally et al. (2009) to rate candidate companies that collect and sell used products. Concerns of three different categories of people (viz., consumers, local government officials, and manufacturers) are considered in this methodology. In Kannan et al. (2009), fuzzy TOPSIS and Interpretive Structural Modeling are used for the problem of selection of the best 3PL. For the solution of the same problem, Saen (2010) develops a DEA-based methodology while Kannan (2009) employs AHP and fuzzy AHP.

In some studies, environmental factors are considered in forward logistic supplier selection problems. Lu et al. (2007) use environmental criteria while developing an AHP-based decision-making methodology for the performance measurement and evaluation of suppliers. Subjective bias in designing a weighting system is reduced by integrating a FL process with the AHP. In Bai and Sarkis (2010), green supplier development programs are evaluated by using a rough set theory-based methodology.

Researchers developed various multicriteria decision-making methodologies for the selection of feasible environmentally conscious manufacturing or RL projects. Sarkis (1998) uses ANP to evaluate environmentally conscious business practices using ANP. In Sarkis (1999), ANP and DEA are integrated to help the decision makers in the evaluation of alternative environmentally conscious manufacturing programs. The use of different methods (viz., Graph Theory and Matrix Approach, Simple Additive Weight Method, AHP and its versions, TOPSIS, and Modified TOPSIS method) was investigated by Rao (2007) by considering the problem presented in Sarkis (1999). Environmentally conscious manufacturing programs are evaluated in Rao (2009) by using an improved compromise ranking method. An ANP and balanced scorecard-based approach is proposed by Ravi et al. (2005) for the analysis of three RL alternatives (viz., Third-Party Demanufacturing (TPD), Symbiotic Logistics Concept (SLC), and Virtual Reverse Logistics Network (VRL)) for PCs. In Ravi et al. (2008), alternative RL projects are evaluated by integrating ANP and Zero One GP.

## 18.4 Conclusions

In this chapter, an AHP model was presented for selecting third-party logistics providers. In the previous section, an overview of the recent literature on third-party reverse logistics provider selection, a green supplier, and project selection were given.

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# 19

# *Performance Measurement*

## 19.1 The Issue

Performance measurement is an important issue in manufacturing organizations. The management can understand the state of the manufacturing system and take appropriate action for maintaining competitiveness based on the observed values of various performance measures. We list the generic functions of manufacturing performance measures here (Hon, 2005):

- They reflect the current state of the manufacturing system.
- They monitor and control operational efficiency.
- They drive the improvement program.
- They measure the effectiveness of manufacturing decisions.

Lead time, production rate, utilization, and work in process inventory level are commonly used manufacturing performance measures. Queuing theory is also used to study the performance of manufacturing systems. For complex systems, simulation is the best tool for performance measurement. All of these performance measures and tools can also be used in remanufacturing systems. In this chapter, we first present the expressions for the various performance measures. An example is also provided to illustrate the calculation of these metrics for a remanufacturing system. Then a case study illustrating the use of queuing theory for performance measurement of remanufacturing systems is presented. Next, an overview of other remanufacturing performance measurement tools is given.

## 19.2 Performance Metrics

In this section, we present some metrics commonly used in manufacturing systems. These metrics can also be used in remanufacturing systems with slight modifications.

### 19.2.1 Production Rate

Production rate is the number of work units completed by a processing center per hour. Cycle time should be determined first while calculating production rate. Cycle time can be calculated using the following expression:

$$CT = OT + PHT + THT \tag{19.1}$$

where $CT$ is the cycle time, $OT$ is the time associated with processing, disassembly or assembly, $PHT$ is part handling time, and $THT$ is tool handling time.

We can determine the production rate considering different types of production (viz., batch production, job shop production, and mass production).

In *batch production*, the time to process a batch involving $Q_b$ work units can be determined as

$$BT = ST + Q_b \cdot CT \tag{19.2}$$

where $BT$ is the batch production time, $ST$ is the setup time for the batch, $Q_b$ is the batch quantity, and $CT$ is the cycle time per work unit. Average production time per work unit, $PT$, can be calculated as follows:

$$PT = \frac{BT}{Q_b} \tag{19.3}$$

Finally, hourly production rate, $PR$, can be determined by taking the reciprocal of production time and multiplying this expression by 60.

$$PR = \frac{60}{PT} \tag{19.4}$$

The same formulas can be used for *job shop production* by taking $Q_b = 1$.

In mass production, we have to consider quantity type mass production and flow line mass production separately.

For quantity type mass production, the effects of setup time can be ignored due to large production quantity. Hence, the production rate is equal to the reciprocal of operation cycle time

$$PR \rightarrow CR = \frac{60}{CT} \tag{19.5}$$

where $CR$ is the operation cycle rate, and $CT$ is the operation cycle time.

For flow line mass production, the effects of setup time can be neglected, too. The cycle time is calculated by adding the transfer time of work units between stations to the longest processing time. This can be mathematically written as follows:

$$CT = TT + \text{Max } OT \tag{19.6}$$

where $CT$ is the cycle time of the production line (min/cycle), $TT$ is the transfer time of work units between stations in a cycle (min/cycle), and Max $OT$ is the maximum of the operation times for all stations on the line (min/cycle). Production rate will be equal to the reciprocal of cycle time

$$PR \rightarrow CR = \frac{60}{CT} \tag{19.7}$$

### 19.2.2 Production Capacity

Production capacity is the total output that can be manufactured by a facility in a given period (viz., week, month, or year) with available resources (e.g., employment levels). The number of hours a plant operates in a week is an important factor in the calculation of capacity. If a plant operates 7 days a week and 24 hours a day, the maximum time available will be 168 hours/week. The expression for production capacity can be given as follows:

$$PC = N_m \cdot N_s \cdot H_s \cdot PR \tag{19.8}$$

where $PC$ is the weekly production capacity, $N_m$ is the number of parallel work stations, $N_s$ is the number of shifts per week, $H_s$ is the number of hours in a shift, and $PR$ is the hourly production rate of each parallel work center. In this equation, it is assumed that $PR$ is same for all machines.

If $N_o$ operations with a new setup on either the same or a different machine are required to manufacture each work unit, then the following expression should be used:

$$PC = \frac{N_m \cdot N_s \cdot H_s \cdot PR}{N_o} \tag{19.9}$$

### 19.2.3 Utilization

Utilization can be defined as the ratio of the output of a production facility to its capacity. This can be expressed as follows:

$$UT = \frac{Q_p}{PC} \tag{19.20}$$

where $UT$ is the utilization, $Q_p$ is the actual quantity produced during a given time period, and $PC$ is the production capacity in the same time period.

### 19.2.4 Availability

Availability, $A$, is commonly used to measure the reliability of manufacturing equipment. It can be defined using two other reliability terms (viz., mean time between failures [MTBF] and mean time to repair [MTTR]) as follows:

$$A = \frac{MTBF - MTTR}{MTBF} \tag{19.21}$$

### 19.2.5 Manufacturing Lead Time

Manufacturing lead time is the total time spent on the production of a part or a product through the plant. It involves operation times as well as any nonoperation time due to delays, reliability problems, etc. The following expression can be used to calculate the lead time.

$$LT_j = \sum_{i=1}^{O_j} (ST_{ji} + Q_{p_j} \cdot CT_{ji} + NOT_{ji}) \tag{19.22}$$

where $LT_j$ is an average manufacturing lead time of part or product $j$, $ST_{ji}$ is the setup time for operation $i$, $Q_{p_j}$ is the batch size for part or product $j$, $CT_{ji}$ is the operation cycle time for operation $i$, $NOT_{ji}$ is the nonoperation time associated with operation $i$, and $i$ is the operation sequence index ($I = 1, 2, \ldots, O_j$).

If it is assumed that all setup times, operation cycle times, and nonoperation times are equal for all the machines, then lead time can be determined using the following expression:

$$LT = O \cdot (ST + Q_p \cdot CT + NOT) \tag{19.23}$$

where $LT$ is an average manufacturing lead time of a part or product, and $O$ is the total number machines.

For the case of job shop production ($Q_p = 1$), the following equation can be used to calculate the manufacturing lead time:

$$LT = O \cdot (ST + CT + NOT) \tag{19.24}$$

### 19.2.6 Work-in-Process

Work-in-process (WIP) consists of unfinished parts or products that are either being processed or waiting in a queue or storage. An approximate expression for WIP can be given as follows (Groover, 2008):

$$WIP = \frac{A \cdot UT \cdot PC \cdot LT}{N_s \cdot H_s} \tag{19.25}$$

Where $WIP$ is the work-in-process in the facility (pieces), $A$ is the availability, $UT$ is the utilization, $PC$ is the production capacity of the facility (pieces/week), LT is the manufacturing lead time (weeks), $N_s$ is the number of shifts per week (shift/week), and $H_s$ is the number hours per shift (hr/shift).

The following numerical example adapted from Groover (2008) illustrates the use of the above formulas in a remanufacturing system.

### 19.2.7 Numerical Example

In a certain remanufacturing shop, an average of twenty new orders is started each week. On average, an order consists of thirty parts that are processed sequentially through eight machines in the factory. The operation time per machine for each part is 12 minutes. The nonoperation time per order at each machine averages 6 hours and the required setup time per order is 2 hours. There are a total of twenty machines in the shop working in parallel. Each of the machines can be set up for any type of job processed in the shop. Only 70% of the machines are operational at any time (the other 30% are in repair or maintenance). The shop operates 120 hours per week. According to this information,

1. What is the lead time for an average order?
2. What is the weekly remanufacturing shop capacity?
3. What is the utilization of the remanufacturing shop?
4. What is the average level of work-in-process in the plant?

Solution:

1. $LT = 8 \cdot (2 + 600 \cdot 0.20 + 6) = 160$ hour/order
2. $PT = (2 + 60 \cdot 0.20)/60 = 14/50 = 0.28$ hour/part, $PR = 3.57$ parts/hour

   $PC = (20 \cdot 0.70 \cdot 120 \cdot 3.57)/8 = 749.7$ parts/week
3. In order to determine the utilization, we have to determine the total number of parts launched per week as follows:

   $$\text{Parts launched per week} = 20 \times 30 = 600$$

   Then utilization is determined as follows:

   $$UT = 600/749.7 = 80\%$$
4. $WIP = (160 \cdot 749.7 \cdot 0.80)/120 = 799.68$ parts

## 19.3 Use of Queuing Theory for Performance Measurement

Queuing theory can be used as a performance measurement tool for remanufacturing systems since it reduces the time required for building models of existing systems and greatly simplifies the modeling process in general

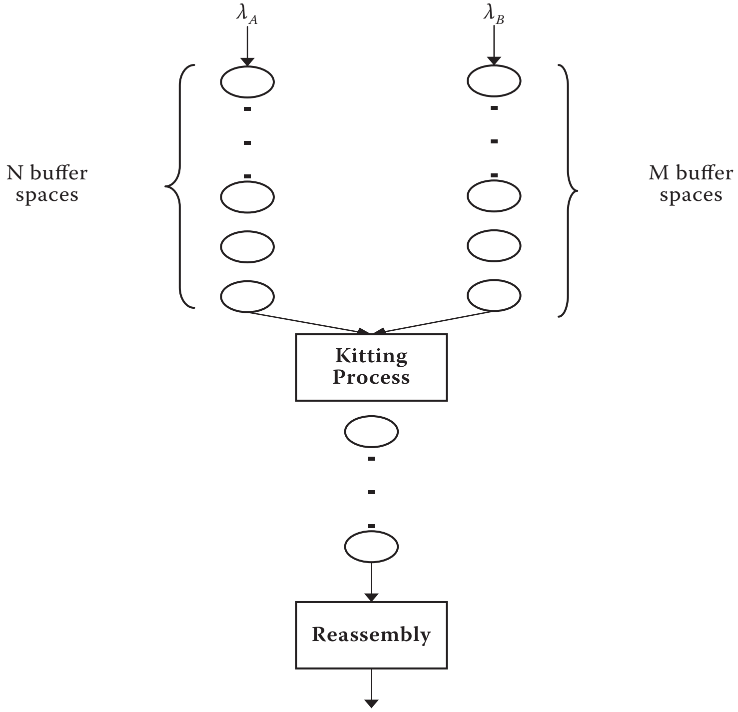

**FIGURE 19.1**
Kitting process.

(Guide and Gupta, 1999). In this section, we model the kitting process of a remanufacturing system using queuing theory.

Figure 19.1 presents the kitting process. According to this figure, parts $A$ and $B$ arrive from the disassembly process in two separate streams with rates $\lambda_A$ and $\lambda_B$, respectively, and form separate queues. One unit of part $A$ and one unit of part $B$ are required to complete a kit. The kits then join a single queue for reassembly. The kitting process can be approximated as a double ended finite buffered queue.

We assume that parts $A$ arrive at the kitting area in a Poisson fashion with mean rate $\lambda_A$ and form a queue if parts $B$ are not available. Parts $B$ also arrive at the kitting area in a Poisson stream with mean rate $\lambda_B$, and pick up one unit of part $A$ from the queue, if any, or else form a queue. Thus, at any given time, there is either a queue of parts $A$ or one of parts $B$ or of neither. Assume that there is a limited buffer space—$N$ units of parts $A$ or $M$ units of parts $B$. (Note that if either part $A$ or part $B$ arrives and finds the buffer full, it is lost to the system. However, by judiciously choosing $N$ and $M$ to be sufficiently large, this problem can be minimized). Let $P_n$ denote the steady state probability that $n$ units of parts $A$ are waiting in the queue. We allow $n$ to vary from $-M$ to $N$. We interpret the value of $n$ as follows. When $n > 0$, it denotes that $n$ units of parts $A$ are waiting. When $n = 0$, it denotes that none of the parts is waiting. When $n < 0$, it denotes that $n$ units of parts $B$ are waiting. The steady state transition equations are given as follows:

$$-\lambda_A P_{-M} + \lambda_B P_{-M+1} = 0 \tag{19.26}$$

$$-(\lambda_A + \lambda_B)P_n + \lambda_A P_{n-1} + \lambda_B P_{n+1} = 0 \quad (-M < n < N) \tag{19.27}$$

$$-\lambda_B P_N + \lambda_A P_{N-1} = 0 \tag{19.28}$$

Solving equations (19.26) through (19.28) recursively, we get

$$P_n = \lambda^{M+n} P_{-M} \quad (-M \le n \le N) \tag{19.29}$$

where $\lambda = \frac{\lambda_A}{\lambda_B}$.

Using the boundary condition

$$\sum_{n=-M}^{N} P_n = 1 \tag{19.30}$$

we get

$$P_{-M} = \frac{1-\lambda}{1-\lambda^{M+N+1}} \qquad \lambda \ne 1 \tag{19.31}$$

Substituting Equation (19.31) into (19.29), we get

$$P_n = \frac{(1-\lambda)\lambda^{M+n}}{1-\lambda^{M+N+1}} \qquad \lambda \ne 1 \quad \text{and} \quad -M \le n \le N \tag{19.32}$$

Taking the limit as $\lambda \to 1$, we get

$$P_n = \frac{1}{M+N+1} \quad \lambda = 1 \quad \text{and} \quad -M \le n \le N \tag{19.33}$$

The probability that there are no parts waiting at the kitting area is

$$P_0 = \frac{(1-\lambda)\lambda^{M}}{1-\lambda^{M+N+1}} \quad \lambda \ne 1 \tag{19.34}$$

$$= \frac{1}{M+N+1} \quad \lambda = 1 \tag{19.35}$$

### 19.3.1 Performance Measures

The probability that there is a queue of parts $A$ is

$$P_A = \sum_{n=1}^{N} P_n$$

$$= \frac{(1-\lambda^N)\lambda^{M+1}}{1-\lambda^{M+N+1}} \qquad \lambda \neq 1 \tag{19.36}$$

$$= \frac{N}{M+N+1} \qquad \lambda = 1 \tag{19.37}$$

The probability that there is a queue of parts $B$ is

$$P_B = \sum_{n=-M}^{-1} P_n$$

$$= \frac{1-\lambda^M}{1-\lambda^{M+N+1}} \qquad \lambda \neq 1 \tag{19.38}$$

$$= \frac{M}{M+N+1} \qquad \lambda = 1 \tag{19.39}$$

The mean queue length of parts $A$ is

$$L_A = \sum_{n=1}^{N} nP_n$$

$$= \frac{\lambda^{M+1}\left\{1-(N+1)\lambda^N + N\lambda^{N+1}\right\}}{(1-\lambda)(1-\lambda^{M+N+1})} \qquad \lambda \neq 1 \tag{19.40}$$

$$= \frac{N(N+1)}{2(M+N+1)} \qquad \lambda = 1 \tag{19.41}$$

The mean queue length of parts $B$ is

$$L_B = \sum_{n=-M}^{-1} -nP_n$$

$$= \frac{M-(M+1)\lambda+\lambda^{M+1}}{(1-\lambda)(1-\lambda^{M+N+1})} \qquad \lambda \neq 1 \tag{19.42}$$

$$= \frac{M(M+1)}{2(M+N+1)} \qquad \lambda = 1 \tag{19.43}$$

Note that due to limited buffer space,

Probability that parts *A* are lost = $P_N$
Probability that parts *B* are lost = $P_{-M}$

Also,

The mean number of parts *A* lost per unit time = $\lambda_A P_N$
The mean number of parts *B* lost per unit time = $\lambda_B P_{-M}$

Note that Little's formula is also valid here. Thus,

$$L_A = \lambda_A W_A \quad \text{and} \quad L_B = \lambda_B W_B$$

where $W_A$ and $W_B$ are mean waiting times for parts *A* and parts *B*, respectively.

### 19.3.2 Example

For $\lambda_A = 2$, $\lambda_B = 5$, $N = 7$, and $M = 5$, the performance measure values can be calculated for the kitting process as follows:

$$\lambda = \frac{2}{5} = 0.40$$

$$P_A = \frac{(1 - 0.40^7)0.40^{5+1}}{1 - 0.40^{5+7+1}} = 0.004$$

$$P_B = \frac{1 - 0.40^5}{1 - 0.4^{5+7+1}} = 0.990$$

$$L_A = \frac{0.4^{5+1}\left\{1 - (7+1)\cdot 0.4^7 + 7\cdot 0.4^{7+1}\right\}}{(1 - 0.4)(1 - 0.4^{5+7+1})} = 0.000$$

$$L_B = \frac{5 - (5+1)\cdot 0.4 + .4^{5+1}}{(1 - 0.4)(1 - 0.4^{5+7+1})} = 4.340$$

Probability that parts *A* are lost = $P_N = 0.000$
Probability that parts *B* are lost = $P_{-M} = 0.600$
The mean number of parts *A* lost per unit time = $2 \cdot 0.000 = 0$
The mean number of parts *B* lost per unit time = $5 \cdot 0.600 = 3$

## 19.4 Other Models

General formulas given in the beginning of this chapter and queuing theory can be used if the remanufacturing system being evaluated is not too complex. For complex remanufacturing systems involving many variables, the best performance measurement tool is simulation. Georgiadis and Vlachos (2004) present a system dynamics simulation (SDS) model to analyze the long term behavior of a closed-loop supply chain involving remanufacturing. They analyze the impact of various remanufacturing capacity expansion policies on system behavior.

Hou and Zhang (2005) employ queuing theory for the performance analysis of a remanufacturing system consisting of a disassembly shop, a remanufacturing shop, an assembly shop, and a warehouse. As a result of this analysis, they provide an optimal remanufacturing policy and an immediate demand fill rate calculation method.

Olugu et al. (2011) propose various performance measures to be used in forward and reverse supply chains of the automotive industry. Forward supply chain performance measures involve “greening cost,” “customer perspective,” “level of process management,” “product characteristics”, “management commitment,” “supplier commitment,” “traditional supply chain cost,” “responsiveness,” “quality,” and “flexibility,” while “recycling cost,” “customer involvement,” “material features,” “management commitment,” “supplier commitment,” and “recycling efficiency” are proposed for reverse supply chains. According to the results of the study, the most crucial measure was customer perspective while the most applicable one was traditional supply chain cost for the forward chain. Management commitment was the top reverse chain performance measure considering both importance and applicability.

## 19.5 Conclusions

In this chapter, first, the applicability of manufacturing-related performance measures in remanufacturing systems was discussed. Then the use of queuing theory in performance measurement of remanufacturing systems was demonstrated. Finally, recent literature was reviewed in the previous section.

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# Part IV

# Processing Issues

# 20

# Disassembly

## 20.1 The Issue

Disassembly can be defined as the systematic separation of an assembly into its components, subassemblies or other groupings (Lambert and Gupta, 2005; McGovern and Gupta, 2011). All product recovery options (viz., remanufacturing, recycling, and disposal) require some level of disassembly. It is an important process in material and product recovery since it allows for the selective separation of desired parts and materials. The following subsections explain the main issues in disassembly, namely, scheduling, sequencing, line balancing, disassembly to order systems, ergonomics, and automation.

### 20.1.1 Scheduling

Disassembly scheduling is the scheduling of the ordering and disassembly of EOL products to fulfill the demand for the parts or components over a planning horizon (Gupta and Taleb, 1994; Veerakamolmal and Gupta, 1998a; Lee and Xirouchakis, 2004).

### 20.1.2 Sequencing

Disassembly sequencing deals with the problem of determining the best order of operations in the separation of a product into its constituent parts or other groupings (Dong and Arndt, 2003; Moore et al., 1998). If an effective disassembly sequence can be determined for a product, the disassembly tasks can be performed with minimum amount of resources (viz., equipment, money, and time). Moreover, the quality of materials recovered and automation level of the disassembly process are increased (Gungor and Gupta, 2001a).

In this chapter, we present two heuristic approaches for disassembly sequencing. The first approach uses disassembly tree representation of the product together with disassembly times for each task. The second approach needs information on the precedence relationships among the components of the product, as well as the difficulty ratings of each component that defines the difficulty level involved in the removal of the components.

### 20.1.3 Line Balancing

Disassembly operations can be performed at a single workstation, in a disassembly cell or on a disassembly line. Although a single workstation and disassembly cell are more flexible, the highest productivity rate is provided by a disassembly line. Moreover, the disassembly line is more suitable for automated disassembly (Gungor and Gupta, 2001b). However, it must be balanced to ensure its efficiency. We can define disassembly line balancing as the assignment of disassembly tasks to a set of ordered disassembly stations while satisfying the disassembly precedence constraints and minimizing the number of stations needed and the variation in idle times between all stations (Altekin et al., 2008; McGovern and Gupta, 2007b).

### 20.1.4 Disassembly-to-Order Systems

In a disassembly-to-order system, the objective is to determine the best combination of multiple products to selectively disassemble to meet the demand for items and materials considering various physical, financial, and environmental constraints and goals.

### 20.1.5 Ergonomics

Ergonomic factors must be considered in the design of a disassembly process due to the hands-on nature of disassembly. In addition, ergonomic factors should also be considered while designing the products. Avoidance of these factors creates various problems and reduces worker efficiency. Some ergonomic problems associated with a disassembly line are as follows (Kazmierczak et al., 2004; Kazmierczak et al., 2005; Kazmierczak et al., 2007):

- The tasks may be monotonous (i.e., some parts need to be disassembled from all products).
- Some components may be broken, rusted, or dirty.
- There may be frequent tool changes.
- Walking and lumbar peak loads tend to be high when compared with assembly work.

Disassembly ergonomics deals with the above problems by developing special tools and/or redesigning the disassembly workplace. Evaluating the ease of disassembly of products can also be considered as a part of disassembly ergonomics.

### 20.1.6 Automation

Today, the level of automation in assembly systems is very high. However, even though the degree of automation in disassembly is very low, some pilot or demonstration disassembly automation projects are being pursued, especially in research institutes. Disassembly operations are usually carried out manually and sometimes mechanized (Kopacek and Kopacek, 2006). There is a need for high-level automation especially for electric/electronic devices due to the dramatic increase in the amount of their scrap.

## 20.2 First Model (Scheduling Heuristic)

Kim (2005) developed an exact algorithm for disassembly scheduling of a two-level disassembly product structure. In this structure, components are located in the first level while the second level represents the root or product itself. A representative two-level disassembly structure is provided in Figure 20.1.

The aim of the proposed heuristic is to determine the disassembly schedule of the root item to meet the demand for components over a planning horizon based on the minimization of the total cost, which includes setup and inventory holding costs.

### 20.2.1 Integer Linear Programming Formulation

An integer linear programming formulation of the problem can be written as follows:

$$Minimize = \sum_{t=1}^{T} S_t \cdot X_t + \sum_{i=1}^{N} \sum_{t=1}^{T} H_{it} \cdot I_{it} \tag{20.1}$$

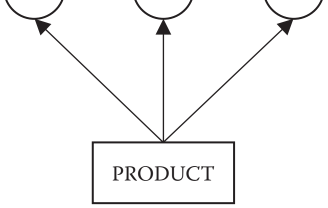

**FIGURE 20.1**
A two-level disassembly product structure.

subject to

$$
\begin{array}{ll}
I_{it} = I_{i,t-1} + A_i \cdot X_t - D_{it} & \text{for } i = 1,2, \ldots, N \text{ and } t = 1,2, \ldots, T \\
Q_t \leq M \cdot X_t & \text{for } t = 1,2, \ldots, T \\
I_{it} \geq 0 \quad \text{and integer} & \text{for } i = 1,2, \ldots, N \text{ and } t = 1,2, \ldots, T \\
Q_t \geq 0 \text{ and integer} & \text{for } t = 1,2, \ldots, T \\
X_t \in \{0,1\} & \text{for } t = 1,2, \ldots, T
\end{array}
$$

where $i$ is the index for leaf items ($i = 1,2, \ldots, N$), $t$ is the index for periods ($t = 1,2, \ldots, T$), $I_{it}$ is the inventory level for item $i$ at the end of period $t$, $A_i$ is the yield of item $i$ resulting from the disassembly of one root item, $X_t$ is the binary variable indicating whether the disassembly of the root item occurs in period $t$ or not (1 = Disassemble; 0 = Do not disassemble), $S_t$ is the setup cost associated with disassembly of root item in period $t$, $H_{it}$ is the holding cost per item $i$ in period $t$, $D_{it}$ is the demand for item $i$ in period $t$, $Q_t$ is the number of root items disassembled in period $t$, and $M$ is an arbitrary large number.

In this formulation, the objective function involves the sum of setup and inventory holding costs. The first constraint defines the inventory level of leaf items at the end of each period and ensures that at the end of each period, the inventory is equal to that at the end of the previous period, increased by the disassembly quantity of the root item multiplied by the yield from the root item in the period, and decreased by the demand quantity in the period. The second constraint guarantees that a setup cost in a period is incurred whenever there is at least one disassembly operation in the period.

### 20.2.2 Development of an Exact Algorithm

A dynamic programming-based algorithm was developed by decomposing the problem into subproblems. Each subproblem is solved recursively, starting from the 1-period subproblem and ending with the $T$-period subproblem. Here, the $t$-period subproblem denotes the subproblem from period 1 to $t$. The demands of the leaf items from period $j$ to $t$ ($1 \leq j \leq t$) are satisfied in period $j$ and the disassembly quantity in period $j$, $Q_j$, can be determined as

$$Q_j = \max_{i=1,2,\ldots,N} \sum_{k=j}^{t} D_{ik} - I_{i,j-1} \Big/ A_i \tag{20.2}$$

where ($j$ – 1)-period subproblem is solved to obtain the inventory $I_{i,j-1}$. In addition, the following expression can be used to determine the inventory level of leaf item $i$ at the end of period $k$ ($j \leq k \leq t$).

$$I_{ik} = \begin{array}{lll} I_{i,k-1} + A_i \cdot X_j - D_{ik} & \textit{for} & k = j \\ I_{i,k-1} - D_{ik} & \textit{for} & k = j+1, j+2, \ldots, t \end{array} \tag{20.3}$$

Recursive cost function of the dynamic programming model can be given as follows:

$$F(t) = \min_{1 \le j \le t} \sum_{i=1}^{N} \sum_{k=j}^{t} H_{ik} \cdot I_{ik} + s_j + F(j-1) \tag{20.4}$$

where $F(t)$ is the optimal cost function for period 1 through $t$.

Recursive cost function consists of the inventory holding costs (of all leaf items) occurred from period $j$ to $t$, the setup cost (of the root item) occurred in period $j$, and the optimal cost function for period 1 through $j - 1$. Therefore, the optimal solution can be obtained by computing $F(t)$ recursively, starting from period 1 and ending in period $T$.

Based on the above dynamic programming structure, an exact algorithm was proposed. Figure 20.2 presents the flow chart for this algorithm.

### 20.2.3 Numerical Example

In this section, we provide a numerical example to illustrate the application of the heuristic procedure. The example is based on the disassembly structure presented in Figure 20.1. Demand for leaf items, setup, and inventory holding costs for each period can be seen in Table 20.1. It is assumed that there is no initial inventory for any of the leaf items.

#### 1-PERIOD SUBPROBLEM

$$Q_1 = \max_{i=1,2,3} \left\{ (D_{i1} - I_{10})/A_i \right\} = \max \left( \frac{(120-0)}{3}, \frac{(75-0)}{1}, \frac{(59-0)}{2} \right) = 75$$

Using $Q_1$ value, we can calculate the inventory levels of leaf items for the first planning period as follows:

$$I_{1,1} = I_{1,0} + A_1 \cdot Q_1 - D_{1,1} = 0 + 3 \cdot 75 - 120 = 105$$

$$I_{2,1} = I_{2,0} + A_2 \cdot Q_1 - D_{2,1} = 0 + 1 \cdot 75 - 75 = 0$$

$$I_{3,1} = I_{3,0} + A_3 \cdot Q_1 - D_{3,1} = 0 + 2 \cdot 75 - 59 = 91$$

The optimal solution value ($F(1)$) of 1-period subproblem (i.e., the total cost $Cost_{1,1}$ of the 1-period subproblem) can be calculated as follows:

$$F(1) = Cost_{1,1} = \sum_{i=1}^{3} H_{i1} \cdot I_{i1} + s_1 + F(0) = 105 \cdot 2 + 0 \cdot 4 + 91 \cdot 4 + 1100 + 0 = \$1674$$

Since disassembly can take place only in period 1, the last setup period becomes 1 (i.e., $l_1 = 1$) for the 1-period problem.

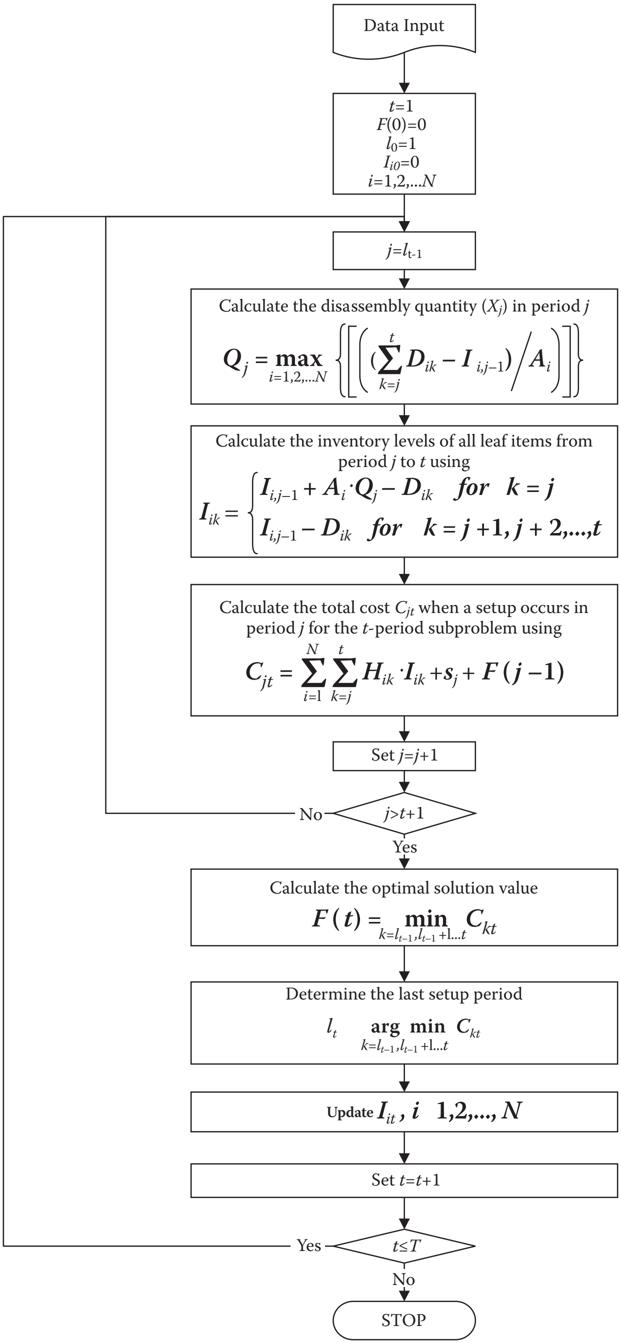

**FIGURE 20.2**
Flow chart for the disassembly scheduling algorithm.

**TABLE 20.1**

Data Set for the Case Example

| | **Planning Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| $D_{1t}$ | 120 | 56 | 47 | 55 | 100 | 120 | 43 | 80 |
| $D_{2t}$ | 75 | 50 | 100 | 38 | 52 | 67 | 102 | 91 |
| $D_{3t}$ | 59 | 42 | 147 | 97 | 68 | 113 | 63 | 93 |
| $S_t$ | 1100 | 1180 | 1200 | 1000 | 1180 | 1220 | 1250 | 1150 |
| $H_{1t}$ | 2 | 4 | 2 | 5 | 1 | 5 | 2 | 2 |
| $H_{2t}$ | 4 | 1 | 2 | 4 | 4 | 2 | 2 | 4 |
| $H_{3t}$ | 4 | 2 | 3 | 5 | 2 | 4 | 3 | 1 |

## 2-PERIOD SUBPROBLEM

In a 2-period subproblem, disassembly can be done only in period 1 or in both periods (i.e., period 1 and period 2). If it is done in only the first period, the disassembly quantity ($X_1$) is determined by considering the demands in periods 1 and 2 as follows.

$$Q_1 = \max \quad \frac{(120+56)}{3}, \frac{(75+50)}{1}, \frac{(59+42)}{2} \quad = 125$$

$$I_{1,1} = 0 + 3 \cdot 125 - 120 = 255$$

$$I_{2,1} = 0 + 1 \cdot 125 - 75 = 50$$

$$I_{3,1} = 0 + 2 \cdot 125 - 59 = 191$$

$$I_{1,2} = 255 - 56 = 199$$

$$I_{2,2} = 50 - 50 = 0$$

$$I_{3,2} = 191 - 42 = 149$$

$$Q_2 = \max \ \frac{(56-105)}{3}, \frac{(50-0)}{1}, \frac{(42-91)}{2}$$

$$Q_2 = 50$$

$$I_{1,2} = 105 + 50 \cdot 3 - 56 = 199$$

$$I_{2,2} = 0 + 50 \cdot 1 - 50 = 0$$

$$I_{3,2} = 91 + 50 \cdot 2 - 42 = 149$$

We can calculate the total cost values for two options as follows:

$$Cost_{1,2} = \sum_{i=1}^{3}\sum_{t=1}^{2} H_{it} \cdot I_{it} + s_1 + F(0)$$

$$= 255 \cdot 2 + 50 \cdot 4 + 191 \cdot 4 + 199 \cdot 4 + 0 \cdot 1 + 149 \cdot 2 + 1100 + 0 = \$3668$$

$$Cost_{2,2} = \sum_{i=1}^{3} H_{i2} \cdot I_{i2} + s_2 + F(1) = 199 \cdot 4 + 0 \cdot 1 + 149 \cdot 2 + 1180 + 1674 = \$3948$$

$$F(2) = \min\,(Cost_{1,2} + Cost_{2,2}) = \$3668$$

According to the above results, the optimal policy is the case when disassembly operation is carried out in period 1. Hence, the last setup period is 1 (i.e., $l_2 = 1$) for the 2-period subproblem.

The same procedure described above is used to solve the subproblems for the remaining periods (i.e., from the 3-period to the 8-period subproblems). The results are summarized in Table 20.2 that shows the total costs $C_{jt}$, the disassembly quantity $Q_t$, the optimal solution value $F(t)$ and the last setup period $l_t$. It must be noted that unnecessary calculations are indicated with dashes in this table.

From Table 20.2, we can determine the optimal solution, denoted in bold in the table, as follows: we consider first the 8-period subproblem, get the optimal disassembly quantity in the last setup period 8 of the subproblem, $Q_8 = 91$, and move to the 7-period subproblem that is the earlier subproblem of the last setup period 8. Then, we get the optimal disassembly quantity in the last setup period of the 7-period subproblem, $Q_7 = 102$, and move to the 6-period subproblem that is the earlier subproblem of the last setup period 7, etc.

**TABLE 20.2**

Optimal Solution Value for Each Subproblem

| Setup | Planning Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| 1 | 1674(75) | **3668(125)** | 8678(225) | — | — | — | — | — |
| 2 | | 3948(50) | 7158(150) | — | — | — | — | — |
| 3 | | | 6658(100) | **10650(138)** | 13887(190) | — | — | — |
| 4 | | | | 11118(38) | 13627(90) | — | — | — |
| 5 | | | | | 13427(52) | **18228(119)** | 24859(221) | — |
| 6 | | | | | | 19263(67) | 24992(169) | — |
| 7 | | | | | | | **23692(102)** | 27790(193) |
| 8 | | | | | | | | **27666(91)** |
| *F(t)* | 1674 | 3668 | 6658 | 10650 | 13427 | 18228 | 23692 | 27666 |
| $l_t$ | 1 | 1 | 3 | 3 | 5 | 5 | 7 | 8 |

**TABLE 20.3**

Setup Periods with Associated Setup Quantities and Resulting Inventories for the Optimal Solution

| | Planning Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| $I_{1t}$ | 255 | 199 | 566 | 511 | 768 | 648 | 967 | 1160 |
| $I_{2t}$ | 50 | 0 | 38 | 0 | 67 | 0 | 0 | 0 |
| $I_{3t}$ | 191 | 149 | 278 | 181 | 351 | 238 | 415 | 504 |
| $Q_t$ | 125 | 0 | 138 | 0 | 119 | 0 | 102 | 91 |

Table 20.3 presents the optimal solution. According to the optimal solution, setups occur in periods 1, 3, 5, 7, and 8 with the corresponding disassembly quantities 125, 138, 119, 102, and 91, respectively.

## 20.3 Second Model (Sequencing Heuristic)

Veerakamolmal and Gupta (1998b) developed a disassembly sequencing heuristic for disassembly process planning. In this section, we first present the steps of this heuristic. Then, the heuristic is applied to an example disassembly sequencing problem.

### 20.3.1 Heuristic Procedure

Step 1. Convert the product structure Bill of Materials into a Disassembly Tree (DT) representation, composed of the root node $S_0$, subassemblies $S_i$, and components $C_i$, ($i = 1,\ldots, n$) starting from the top level down to the leaf nodes.

Step 2. Cluster the tree structure into simple subtree modules using the Modularity Assignment Rule (Veerakamolmal et al., 1997). Employing the well known depth first search algorithm [i], label each subtree $P'$ with an array $\{a[i]\}$ ($i = 1,\ldots, k$), the elements of which are the nodes in the subtree. Set $J = k$, where $J$ is the maximum number of subtrees.

Step 3. Arrange the arrays $\{a[i]\}$ in reverse order such that they are listed from $a[J]$ to $a[1]$.

Step 4. Set counter $Z = J$.

Step 5. Let $N(P')_Y$ be the minimum makespan partial sequence associated with subtree $Y$, and $N_0(P')_Y$ be its corresponding root node. Each individual subassembly is sequenced as follows:

$$N(P')_Y = \{N_0(P')_Y, N_1(P')_Y, N_2(P')_Y \}$$

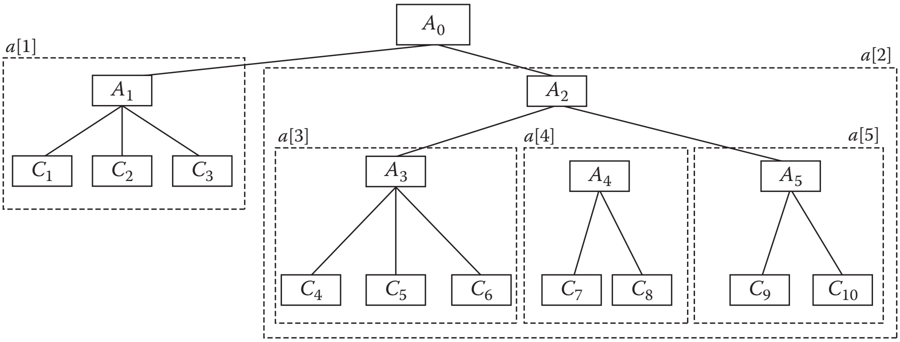

**FIGURE 20.3**
Product structure.

where $N_1(P')_Y$ represents a partial sequence of $N(P')_Y$ arranged according to the shortest start-lag time for processing, $N_2(P')_Y$ represents a partial sequence of $N(P')_Y$ arranged according to the longest stop-lag time for disassembly. Note that the memberships of the elements in $N_1(P')_Y$ and $N_2(P')_Y$ are determined as follows: If $L_j \leq L_i$, the element belongs to $N_1(P')_Y$ and if $L_j > L_i$, the element belongs to $N_2(P')_Z$

Step 6. If $Y \neq 0$, set $Y = Y - 1$ and go to Step 4, otherwise $N(P')_0$ represents the final optimal makespan of the process. Stop.

### 20.3.2 Case Example

The assembly structure presented in Figure 20.3 is considered here to illustrate the use of the heuristic. This structure involves ten components grouped into five modules. In disassembly sequence, first $A_0$ is disassembled to separate subassembly modules from each other. Following disassembly, retrieval operations are immediately performed on each component. Table 20.4 presents disassembly and retrieval process times. The disassembly tree is given in Figure 20.3.

The disassembly tree can be disaggregated into a simple subtree *a*[1] and a complex subtree *a*[2] using the modularity assignment rule. Since there are simple subtrees in subtree *a*[2], it can further be disaggregated into subtrees

**TABLE 20.4**

Disassembly and Processing Times (minutes)

| **Module** | $A_0$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Disassembly time ($DT_i$) | 2 | 2 | 1 | 4 | 5 | 3 | | | | |
| Component | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ | $C_{10}$ |
| Processing time ($PT_j$) | 1 | 1 | 2 | 2 | 2 | 1 | 2 | 1 | 2 | 2 |

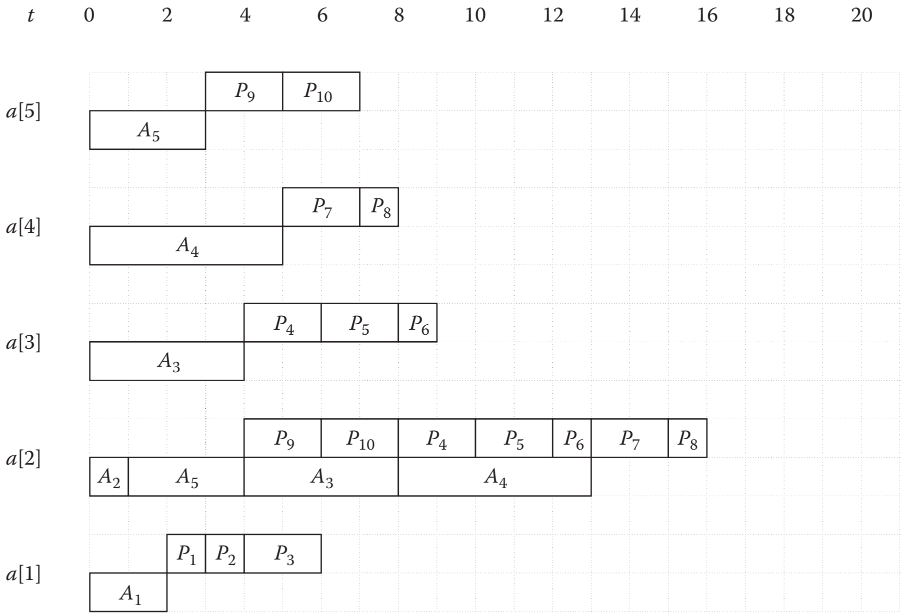

**FIGURE 20.4**
Disassembly sequence for each subassembly *a*[i].

*a*[3], *a*[4], and *a*[5]. Then the partial minimum makespan schedules for all simple sub-trees are determined as can be seen in Figure 20.4.

We start idle time analysis with the simple subtrees of subtree *a*[2]. The idle times in the disassembly process and retrieval process ($L_i$, $L_j$) for the subtrees *a*[3], *a*[4], and *a*[5] are {(5,4), (3,5), and (4,3)}, respectively (Figure 20.4). Based on these values, we can determine the sequence for *a*[2] (which is made up of *a*[3], *a*[4], and *a*[5]) as follows:

$$N_0(P')_2 = A_2$$
$$N_1(P')_2 = \{a[5], a[3]\}, \quad (\because L_j \le L_i)$$
$$N_2(P')_2 = \{a[4]\}. \quad (\because L_j > L_i)$$

Hence, for subassembly *a*[2], the partial sequence to disassemble is as follow:

$$N(P')_2 = \{A_2, a[5], a[3], a[4]\}.$$

Since *a*[1] itself is a simple subtree, its partial disassembly sequence can directly be determined as follows:

$$N(P')_1 = \{a[1]\}.$$

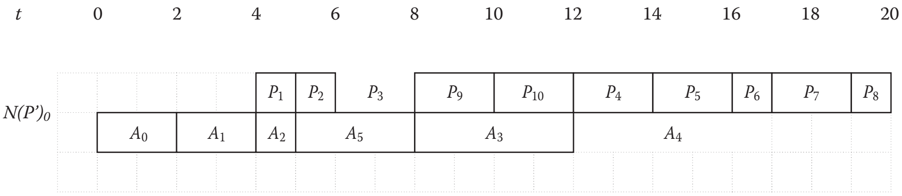

**FIGURE 20.5**
Disassembly sequence of the product *P*.

The optimal makespan sequence $N(P')_0$ is obtained by integrating the partial sequences of $a[1]$ and $a[2]$. Thus, the resulting idle times in the disassembly process and retrieval process $(L_i, L_j)$ for $a[1]$ and $a[2]$ are {(4, 2) and (3,4)}, respectively (Figure 20.4). Hence:

$$
\begin{aligned}
&N_0(P')_0 = A_0 \\
&N_1(P')_0 = \{a[1]\}, \qquad\qquad (\because L_j \le L_i) \\
&N_2(P')_0 = \{a[2], a[5], a[3], a[4]\}, (\because L_j > L_i)
\end{aligned}
$$

This leads to

$$N(P')_0 = \{A_0, a[1], a[2], a[5], a[3], a[4]\}.$$

The complete process plan with a minimum makespan of 20 minutes (Figure 20.5) can be written as follows:

Disassembly Process : $A_0 \rightarrow A_1 \rightarrow A_2 \rightarrow A_5 \rightarrow A_3 \rightarrow A_4$
Retrieval Phase: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_9 \rightarrow P_{10} \rightarrow P_4 \rightarrow P_5 \rightarrow P_6 \rightarrow P_7 \rightarrow P_8$

## 20.4 Third Model (Sequencing Heuristic)

The disassembly sequencing heuristic proposed by Gungor and Gupta (1997) gives a near-optimal disassembly sequence for a product. In the heuristic procedure, the efficiency of a disassembly sequence is evaluated based on its total disassembly time (TDT) which is calculated as follows:

$$TDT = \sum_{i=1}^{N} (T_{S_{i-1}, S_i}) \tag{20.5}$$

where

$$T_{S_{i-1},S_i} = t_{S_i} \cdot (1 + \delta + \lambda) \quad (i{=}1, 2, \ldots, N) \tag{20.6}$$

where

$T_{S_{i-1},S_i}$ : Adjusted disassembly time for $S_i$ provided that it is disassembled just after $S_{i-1}$

$t_{S_i}$ : Disassembly time for $S_i$

$\delta$: Factor for direction change. It is determined as follows:

$$\delta = \begin{array}{ll} 0.1 - 1, & \text{if there is a direction change while disassembling } S_i \text{ after } S_{i-1} \\ 0, & \text{otherwise} \end{array} \tag{20.7}$$

$\lambda$: Factor for joint type change. It is determined as follows:

$$\lambda = \begin{array}{ll} 0.1 - 1, & \text{if there is a change in joint type while disassembling } S_i \text{ after } S_{i-1} \\ 0, & \text{otherwise} \end{array} \tag{20.8}$$

$N$: Number of subassemblies in the product

### 20.4.1 Heuristic Procedure

First, two lists are created for disassembled ($DC$ = {}) and nondisassembled components ($NDC$ = {}). Then, $M$ tables, $P(1)$, $P(2)$ … $P(\mathrm{M})$ are created by listing subassemblies in the ascending order of their average difficulty ratings. $M$ is the number of different joint types existed in the product. After this initialization stage, the procedure given as a flow chart in Figure 20.6 is implemented.

### 20.4.2 Numerical Example

In this section, the heuristic procedure is applied to a conceptual product involving eighteen components. Predecessors, disassembly direction, joint type, and average difficulty rating for each component can be seen in Table 20.5. Since there are two types of joints in the product ($M$ = 2), two tables must be prepared before implementing the heuristic procedure. The first table (see Table 20.6) involves components with only snap-fit joints

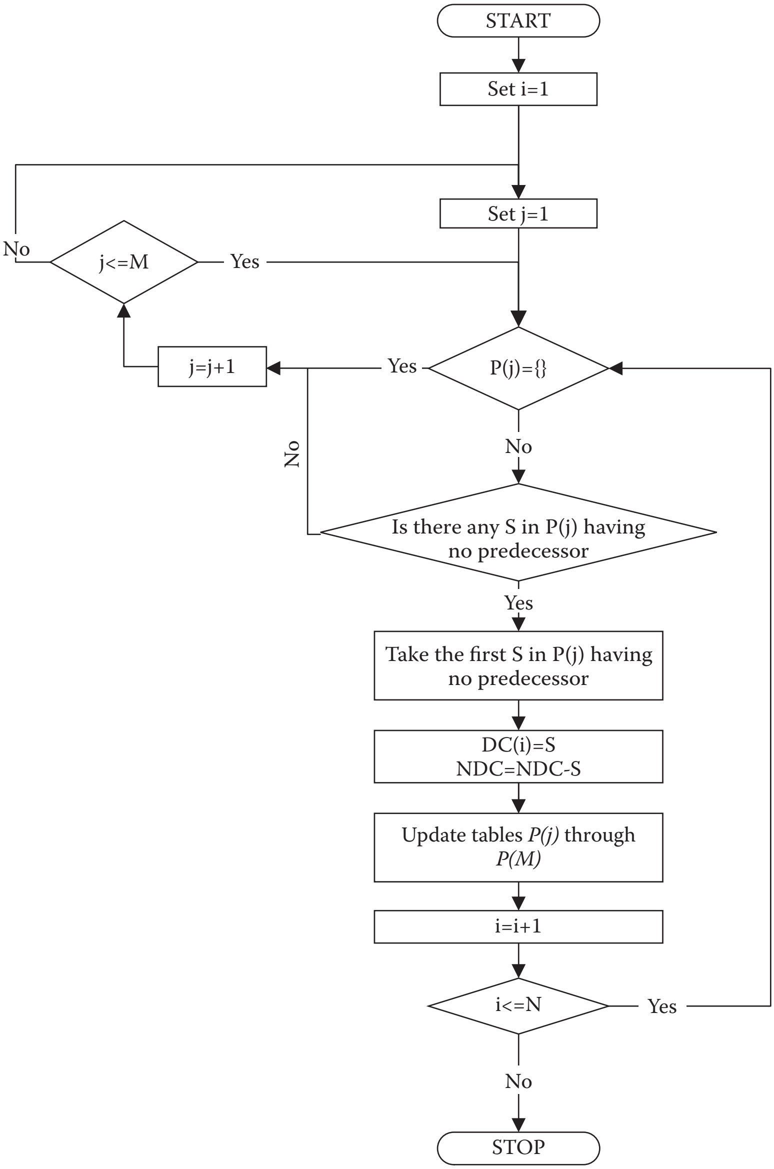

**FIGURE 20.6**
Flow chart of the heuristic procedure.

**TABLE 20.5**

Specifications for Subassemblies

| Component Code | Predecessors | Disassembly Direction | Joint Type | Average Difficulty Rating |
|---|---|---|---|---|
| A | — | X | Screws | 1.5 |
| B | — | –X | Snap fit | 2 |
| C | A,B | X | Snap fit | 2.5 |
| D | C | Y | Screws | 1 |
| E | — | –Y | Screws + snap fit | 0.5 |
| F | D | Z | Screws + snap fit | 1.4 |
| G | E,F | Z | Screws | 3 |
| H | C | X | Snap fit | 3.2 |
| I | G | Y | Screws + snap fit | 3.5 |
| J | — | –X | Screws + snap fit | 3.6 |
| K | C,G | Z | Snap fit | 2.2 |
| L | J | X | Screws | 2.3 |
| M | K,L | –X | Screws | 2.7 |
| N | M | Z | Snap fit | 1.5 |
| O | — | Y | Screws + snap fit | 1.3 |
| P | J,K | X | Screws + snap fit | 1.2 |
| Q | K,M | X | Snap fit | 1 |
| R | J,G | –X | Snap fit | 0.8 |

while the components mounted either with screws only or with snap-fit joints and screws are listed in the second table (see Table 20.7).

Upon the application of the procedure, the disassembly sequence presented in Table 20.8 was determined. With a $\delta$ value of 0.3 and a $\lambda$ value of 0.5, the proposed disassembly sequence results in a TDT of 316.7 seconds. In order to demonstrate the performance of the heuristic, we considered a randomly picked disassembly sequence presented in Table 20.9. TDT for this sequence is 67.2 seconds higher than the proposed disassembly sequence.

**TABLE 20.6**

Subassemblies Involving Only Snap-Fit

| Subassembly Code | Predecessors | Disassembly Direction | Joint Type | Average Difficulty Rating |
|---|---|---|---|---|
| R | J,G | –X | Snap fit | 0.8 |
| Q | K,M | X | Snap fit | 1 |
| N | M | Z | Snap fit | 1.5 |
| B | — | –X | Snap fit | 2 |
| K | C,G | Z | Snap fit | 2.2 |
| C | A,B | X | Snap fit | 2.5 |
| H | C | X | Snap fit | 3.2 |

**TABLE 20.7**

Subassemblies Involving Screws and Snap-Fit

| Subassembly Code | Predecessors | Disassembly Direction | Joint Type | Average Difficulty Rating |
|---|---|---|---|---|
| E | — | –Y | Screws + snap fit | 0.5 |
| D | C | Y | Screws | 1 |
| P | J,K | X | Screws + snap fit | 1.2 |
| O | — | Y | Screws + snap fit | 1.3 |
| F | D | Z | Screws + Snap fit | 1.4 |
| A | — | X | Screws | 1.5 |
| L | J | X | Screws | 2.3 |
| M | K,L | –X | Screws | 2.7 |
| G | E,F | Z | Screws | 3 |
| I | G | Y | Screws + snap fit | 3.5 |
| J | — | –X | Screws + snap fit | 3.6 |

**TABLE 20.8**

Proposed Disassembly Sequence

| DS | DD | JT | $t_{S_i}$ | δ | λ | $T_{S_{i-1},S_i}$ |
|---|---|---|---|---|---|---|
| B | –X | SF | 60 | 0 | 0 | 60 |
| E | Y | SCF | 10 | 0.3 | 0.5 | 18 |
| O | Y | SCF | 20 | 0 | 0 | 20 |
| A | X | SC | 12 | 0.3 | 0.5 | 21.6 |
| C | X | SF | 15 | 0 | 0.5 | 22.5 |
| H | X | SF | 25 | 0 | 0 | 25 |
| D | Y | SC | 4 | 0.3 | 0.5 | 7.2 |
| F | Z | SCF | 6 | 0.3 | 0.5 | 10.8 |
| G | Z | SC | 10 | 0 | 0.5 | 15 |
| K | Z | SF | 10 | 0 | 0.5 | 15 |
| I | Y | SCF | 5 | 0.3 | 0.5 | 9 |
| J | –X | SCF | 15 | 0.3 | 0 | 19.5 |
| R | –X | SF | 10 | 0 | 0.5 | 15 |
| P | X | SCF | 4 | 0.3 | 0.5 | 7.2 |
| L | X | SC | 8 | 0 | 0.5 | 12 |
| M | –X | SC | 15 | 0.3 | 0 | 19.5 |
| Q | X | SF | 5 | 0.3 | 0.5 | 9 |
| N | Z | SF | 8 | 0.3 | 0 | 10.4 |
|  |  |  |  |  | TDT | 316.7 |

**TABLE 20.9**

Randomly Picked Disassembly Sequence

| DS | DD | JT | $t_{s_i}$ | $\delta$ | $\lambda$ | $T_{s_{i-1}, s_i}$ |
|---|---|---|---|---|---|---|
| E | Y | SCF | 10 | 0 | 0 | 10 |
| B | –X | SF | 60 | 0.3 | 0.5 | 108 |
| J | –X | SCF | 15 | 0 | 0.5 | 22.5 |
| A | X | SC | 12 | 0.3 | 0.5 | 21.6 |
| O | Y | SCF | 20 | 0.3 | 0.5 | 36 |
| C | X | SF | 15 | 0.3 | 0.5 | 27 |
| D | Y | SC | 4 | 0.3 | 0.5 | 7.2 |
| F | Z | SCF | 6 | 0.3 | 0.5 | 10.8 |
| G | Z | SC | 10 | 0 | 0.5 | 15 |
| I | Y | SCF | 5 | 0.3 | 0.5 | 9 |
| K | Z | SF | 10 | 0.3 | 0.5 | 18 |
| R | –X | SF | 10 | 0.3 | 0 | 13 |
| L | X | SC | 8 | 0.3 | 0.5 | 14.4 |
| M | –X | SC | 15 | 0.3 | 0 | 19.5 |
| N | Z | SF | 8 | 0.3 | 0.5 | 14.4 |
| Q | X | SF | 5 | 0.3 | 0 | 6.5 |
| H | X | SF | 25 | 0 | 0 | 25 |
| P | X | SCF | 4 | 0 | 0.5 | 6 |
| | | | | | TDT | 383.9 |

## 20.5 Fourth Model (Line-Balancing Heuristic)

Gungor and Gupta (2002) developed a heuristic procedure for a simple disassembly line balancing problem (DLBP-S). In this heuristic, a priority function is used to identify the best task to assign a particular workstation. The following assumptions were made while developing the heuristic:

- One product type is disassembled in a paced disassembly line.
- Product supply is infinite.
- Each received product has same configuration (quantity of parts in each product is exactly known).
- Disassembly times are deterministic and known.
- Demand exists for every part of the product (i.e., complete disassembly is required).
- Demand is deterministic with known parameters.
- Disassembled parts can be used in their current conditions to satisfy the demand.

### 20.5.1 Performance Measures

Cycle time of a disassembly line can be written as

$$c = \frac{L}{d_{\max}}, \tag{20.9}$$

where $c$ is the cycle time, $L$ is the duration (or the length) of the planning period (discretely incremented), and $d_{max}$ is the highest demand. $d_{max}$ can be determined as follows:

$$d_{\max} = \max_{i=1,\dots,N} \frac{d_i}{q_i} \tag{20.10}$$

where $d_i$ is the demand for part $i$, $q_i$ is the number of same part $i$ (i.e., quantity of part $i$) in the product, and $N$ is the number of parts of the product, which is equal to the number of tasks, that is, $I = 1, \dots, N$.

$c$ must satisfy the following condition

$$t_i \leq c, \quad i: 1, \dots, N \tag{20.11}$$

where $t_i$ is the time necessary to perform task $i$ (or operation time of $i$).

The following equation can be used to determine the theoretical minimum number of workstations (WSs):

$$M_{\min} = \frac{T}{c} = \frac{\sum_{i=1}^{N} t_i}{c} \tag{20.12}$$

where $M_{min}$ is the minimum number of workstations (the lower bound), $T$ is the cumulative duration of all disassembly tasks, $x$ is the smallest integer $\geq x$.

The maximum number of WSs ($M_{max}$) can be found as

$$M_{max} = N \tag{20.13}$$

Idle time of workstation $k$ ($IT_k$), the difference between the cycle time and workstation time of $k$, can be written as follows:

$$IT_k = c - S_k \tag{20.14}$$

where $S_k$ is the workstation time of $k$ (i.e., total processing time of tasks that have been assigned to workstation $k$). It can be calculated as follows:

$$S_k = \sum t_j, \quad j \in A_k \tag{20.15}$$

where $A_k$ is the set of tasks that have been assigned to workstation $k$.

The idle time of the disassembly line (*IT*) can be written as follows:

$$IT = \sum_{k=1}^{M} IT_k \text{ or } IT = (M \cdot c) - T \tag{20.16}$$

A task *i* must satisfy the following conditions to be called as a candidate task:

- It must not have been assigned already to any earlier workstation, that is,

$$i \quad \bigcup A_m, \quad m = 1, \ldots, k-1. \tag{20.17}$$

- All its predecessors must be completed, that is,

$$\begin{aligned} &r_{ji} = 0, \quad j = 1, \ldots, N; \quad or \\ &r_{ji} = 1, \quad j \in A_m; \quad m = 1, \ldots, k-1; \quad and/or \\ &r_{ji} = d, \quad\; j \in OG_{i,d} \quad \bigcup A_m; \quad m = 1, \ldots, k-1. \end{aligned} \tag{20.18}$$

- Sum of operation time of task *i* and workstation time of *k* must be less than or equal to the cycle time; that is,

$$S_k + t_i \leq c \tag{20.19}$$

### 20.5.2 Priority Function

After identifying the candidate tasks, a priority function is used to determine the candidate tasks to be assigned to the current WS, *k*. Although many factors may be considered while forming the priority function, in this study, the following factors are taken into consideration:

- *Idle Times*: Tasks must be assigned to WSs in a way that maximizes the utilization of WSs. Hence, in order to have a minimum number of WSs, idle times of WSs are considered.
- *Highly demanded parts*: It is desirable that the highly demanded parts are disassembled at the earliest workstation possible; the possibility of getting damaged is higher if the product stays a longer time in the disassembly line.
- *Easily accessible parts preceding the largest number of parts:* Disassembly of a part which is easily accessible and precedes many other parts should be done as soon as possible. By doing this, a better line balance can be achieved due to the increased number of candidate parts in the later iterations of the heuristic.

- *Parts with hazardous contents:* Hazardous material spill from the parts with hazardous contents could result in the unavailability of one or more WSs. In addition, the other demanded parts could be contaminated. In order to prevent these negative consequences, these parts should be disassembled as early as possible.
- *Disassembly movement direction changes:* The number of times a workpiece is reoriented on the disassembly line should be minimized. This results in a smoother disassembly procedure.

The following priority function is used in the heuristic procedure:

$$PF_i = pf(IT_{i,k}) + pf(D_i) + pf(EA_i) + pf(HM_i) + pf(DC_i) \tag{20.20}$$

where

$pf(IT_{i,k})$: This priority value is calculated considering the idle times of the WSs. In order to determine this value, the candidate tasks to be assigned to workstation $k$ are listed in the ascending order based on their $IT_{i,k}$ (idle time of workstation $k$ when task $i$ is assigned to workstation $k$) values. The rank of each task in this list is equal to its priority value.

$pf(d_i)$: This priority value is related to the disassembly of highly demanded parts. In order to determine this value, the candidate tasks are listed in the descending order based on their $d_i$ (demand for part $i$) values. The rank of each task in this list is equal to its priority value.

$pf(EA_i)$: This priority value is related to the parts which are easily accessible and precede many other parts. In order to determine this value, the candidate tasks are listed in the descending order based on their $EA_i$ (number of remaining tasks that task $i$ precedes) values. The rank of each task in this list is equal to its priority value.

$pf(HM_i)$: This priority value is related to the parts containing hazardous materials. In order to determine this value, the candidate tasks are listed in the descending order based on their $HM_i$ values (binary variable representing whether or not disassembly task $i$ belongs to a part with hazardous content). The rank of each task in this list is equal to its priority value.

$pf(DC_i)$: This priority value is related to the changes in disassembly movement direction. In order to determine this value, the candidate tasks are listed in the ascending order based on their $DC_i$ (disassembly direction change or not) values. The rank of each task in this list is equal to its priority value.

The following equations are required for the calculation of $IT_{i,k}$, $HM_i$, and $DC_i$ values:

$$IT_{i,k} = c - (S_k + t_i), \quad i \in CA_k \tag{20.21}$$

where $CA_k$ is the set of candidate tasks that can be assigned to workstation $k$

$$HM_i = \begin{cases} 1, \text{ if task } i \text{ involves the disassembly of a part with} \\ \quad \text{hazardous content} \\ 0, \text{ otherwise} \end{cases} \tag{20.22}$$

$$DC_i = \begin{cases} 1, \text{ if task } i \text{ involves the disassembly of a part which} \\ \quad \text{requires a change in disassembly movement direction} \\ 0, \text{ otherwise} \end{cases} \tag{20.23}$$

## 20.5.3 Heuristic Procedure

The pseudo-code of the heuristic procedure can be written as follows:

```
$k$= 1;                                        /* Create the first work-
                                                  station */
repeat {
        Determine the candidate tasks, $CA_k$;
        If (|$CA_k$| = 0)                      /* There is no candidate
                                                  task */
                $k = k + 1$;                   /* Create another
                                                  workstation */
        If (|$CA_k$| ≠ 0) {                    /* There are candidate
                                                  tasks */
                Determine $F_i$ where $i \in CA_k$   /* Calculate the priority
                                                  function value of each
                                                  candidate */
                $A_k = A_k \cup j$; where $F_j = F_{\min}$   /* Assign task j such that
                                                  j has the minimum
                                                  priority function value
                                                  ($F_{\min}$) */
}
until (all tasks are assigned to workstations)
$M = k$;                                       /* the number of required
                                                  disassembly workstation
                                                  is k */
return ($M$, $A_m$);
}                                              / *end of the algorithm */
```

## 20.5.4 Numerical Example

In this section, we apply the heuristic procedure to a computer disassembly line. Table 20.10 provides the specifications for disassembly tasks associated with a PC. A disassembly precedence matrix is presented in Figure 20.7.

**TABLE 20.10**

Various Specifications for PC Disassembly Tasks

| Task | Task Time | Definition of the Removed Component | Component Demand | Hazardous Material | Direction of Disassembly |
|---|---|---|---|---|---|
| 1 | 12 | Top cover | 300 | No | –x |
| 2 | 15 | Optic disk | 550 | No | X |
| 3 | 10 | Floppy disk | 250 | No | x |
| 4 | 14 | Storage unit | 800 | No | –x |
| 5 | 16 | Back plate | 400 | No | X,–x, y, or –y |
| 6 | 18 | PCI cards | 500 | No | Y |
| 7 | 20 | RAM modules (3) | 900 | No | z |
| 8 | 15 | Power supply | 350 | Yes | –x, x, or y |
| 9 | 24 | Motherboard | 700 | No | Z |

Equation 20.10 is used to calculate the number of products to be disassembled as follows:

$$d_{\max} = \max_{i=1,\ldots,9} \frac{d_i}{\textit{Multiplicity of part } i}$$

$$= \max \left\{ \frac{300}{1}, \frac{550}{1}, \frac{250}{1}, \frac{800}{1}, \frac{400}{1}, \frac{500}{1}, \frac{900}{3}, \frac{350}{1}, \frac{700}{1} \right\} = 800.$$

For an 8-hour shift, $H = 8 \cdot 60 \cdot 60 = 28800$ seconds.

$$c = \frac{28800}{800} = 36 \text{ seconds.}$$

$$R = \begin{array}{c|ccccccccc} & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\ \hline 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 0 & 0 & 0 & 0 & 0 & 0 & -x & 0 & 1 \\ 3 & 0 & 0 & 0 & 0 & 0 & 0 & -x & 0 & 1 \\ 4 & 0 & 0 & 0 & 0 & 0 & 0 & x & 0 & 1 \\ 5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 6 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 8 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{array}$$

**FIGURE 20.7**
Disassembly precedence matrix of a PC.

**TABLE 20.11**

Implementation of the Heuristic for the Example Problem

| Iteration | 1 | 2 | | | | 3 | 4 | | | 5 | | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Station | 1 | 1 | | | | 1 | 2 | | | 2 | | 3 | 3 | 4 | 4 |
| $i \in CA_k$ | 1 | 2 | 3 | 4 | 6 | 3 | 2 | 6 | 7 | 2 | 6 | 6 | 9 | 8 | 5 |
| $t_i$ | 12 | 15 | 10 | 14 | 12 | 10 | 15 | 12 | 20 | 15 | 12 | 12 | 24 | 15 | 16 |
| $IT_{i,k}$ | 24 | 9 | 14 | 10 | 12 | 0 | 21 | 24 | 16 | 1 | 4 | 24 | 0 | 21 | 5 |
| $f(IT_{i,k})$ | 1 | 1 | 4 | 2 | 3 | 1 | 2 | 3 | 1 | 1 | 2 | 1 | 1 | 1 | 1 |
| $d_i$ | 300 | 550 | 250 | 800 | 500 | 250 | 550 | 500 | 900 | 550 | 500 | 500 | 700 | 350 | 400 |
| $f(d_i)$ | 1 | 2 | 4 | 1 | 3 | 1 | 2 | 3 | 1 | 1 | 2 | 1 | 1 | 1 | 1 |
| $EA_i$ | 8 | 2 | 2 | 2 | 2 | 2 | 1 | 2 | 1 | 1 | 2 | 2 | 1 | 1 | 0 |
| $f(EA_i)$ | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 1 | 2 | 2 | 1 | 1 | 1 | 1 | 1 |
| $HM_i$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| $f(HM_i)$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| $DC_i$ | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| $f(DC_i)$ | 1 | 2 | 2 | 1 | 2 | 1 | 1 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 |
| $PF_i$ | 5 | 7 | 12 | 6 | 10 | 5 | 8 | 10 | 7 | 6 | 7 | 5 | 5 | 5 | 5 |
| $A_k$ | {1} | {1,4} | | | | **{1,4,3}** | {7} | | | **{7,2}** | | {6} | **{6,9}** | {8} | **{8,5}** |
| $S_k$ | 12 | 26 | | | | **36** | 20 | | | **35** | | 12 | **36** | 15 | **31** |
| $IT_k$ | 24 | 10 | | | | **0** | 16 | | | **1** | | 24 | **0** | 21 | **5** |

Solution steps for the problem can be seen in Table 20.11. The proposed solution requires four WSs. Assignment of tasks to WSs is as follows:

$$A_1 : \{1,4,3\}$$

$$A_2 : \{7,2\}$$

$$A_3 : \{6,9\}$$

$$A_4 : \{8,5\}$$

Station idle times are $IT_1 = 0$; $IT_2 = 1$; $IT_3 = 0$; $IT_4 = 5$ seconds per product, respectively.

## 20.6 Fifth Model (Goal Programming Model for a DTO System)

Disassembly-to-order problems usually involve more than one objective. That is why multicriteria optimization approaches are commonly applied to these problems. In this section, we present a case study involving the use of preemptive goal programming (PGP) to solve a disassembly-to-order problem. When solved, the model provides the number of reused, recycled, stored, and disposed items as well as the values of a host of other performance measures.

## 20.6.1 Development of Goal Programming Formulation

### *20.6.1.1 The Goals*

We consider four goals. The first goal is the maximization of the overall profit of the DTO system. In goal programming terms, we want profit level to be at its aspiration level and exceed it as much as possible. In order to achieve this mathematically, the negative deviation ($d_1^-$) from the predetermined value $TP^*$ must be minimized to obtain a value equal to zero. We do not put any restrictions on the positive deviation ($d_1^+$) to secure the best profit level. This goal can be formulated as follows:

$$\min d_1^-$$

$$s.t.\ \ TP + d_1^- - d_1^+ = TP^* \tag{20.24}$$

The second goal involves the minimization of procurement cost (*PC*). This is achieved by minimizing positive deviation ($d_2^+$). This goal can be expressed as follows:

$$\min d_2^+$$

$$s.t.\ \ PC + d_2^- - d_2^+ = PC^* \tag{20.25}$$

Minimization of the product take back cost (*TBC*) is the third goal. We can achieve a lower total cost level by determining a better combination of take-back products while securing the satisfaction of demand for components and materials. Mathematically, this can be achieved by forcing the positive deviation ($d_3^+$) from *TBC* to achieve a value equal to zero. This goal can be formulated as follows:

$$\min d_3^+$$

$$s.t.\quad TBC + d_3^- - d_3^+ = TBC^* \tag{20.26}$$

The fourth goal, minimization of the disposal cost (*DC*), is an environmentally conscious goal since it requires the minimization of the number of disposed products, components, and materials. In order to hold this cost to a limitation level, we minimize the positive deviation ($d_4^+$). This can be expressed mathematically as follows:

$$\min d_4^+$$

$$s.t.\quad DC + d_4^- - d_4^+ = DC^* \tag{20.27}$$

We do not provide any weight to the goals. The order in which we present a particular goal above represents its priority order. Hence, maximization of the profit has the highest priority, while the lowest priority goal is the minimization of the disposal cost.

#### 20.6.1.2 Total Profit Value and Related Terms

Total profit (*TP*) can be written as follows:

$$TP = CSR + MSR + SCV - OPC - TBC - DIC - DDC - NDC - STC - REC \tag{20.28}$$

Each term that contributes to the *TP* function is elaborated below.

*CSR*, revenue from component sales, is determined by multiplying the total number of demands for component type *j* ($D_j$) by its corresponding unit resale value ($rv_j$). Therefore,

$$CSR = \sum_j (D_j \cdot rv_j) \tag{20.29}$$

*MSR*, revenue from material sales, is calculated by multiplying the total weight of recycled material type *j* ($WRM_j$) by its corresponding material price per weight ($pm_j$). Therefore,

$$MSR = \sum_j (WRM_j \cdot pm_j) \tag{20.30}$$

Value of stored components, *SCV*, is calculated by multiplying the total number of stored components type *j* ($NSC_j$) by its corresponding unit equivalent value ($sev_j$). Therefore,

$$SCV = \sum_j (NSC_j \cdot sev_j) \tag{20.31}$$

Outside procurement cost (*OPC*) is calculated by multiplying the total number of procured component type *j* ($P_j$) by its corresponding unit procurement cost ($pc_j$). Therefore,

$$OPC = \sum_j (P_j \cdot pc_j) \tag{20.32}$$

*TBC*, take back cost of products, is calculated by multiplying the total number of EOL products type *i* ($NTB_i$) by the corresponding unit take-back cost ($tbc_i$). Therefore,

$$TBC = \sum_i (NTB_i \cdot tbc_i) \tag{20.33}$$

*DIC*, disposal cost, is calculated by multiplying the total number of disposed product type *i* ($NDP_i$), disposed component type *j* ($NDC_j$), and disposed material type *j* ($NDM_j$), by their corresponding unit disposing cost for product type *i* ($dpp_i$), component type *j* ($dpc_j$), and material type *j* ($dpm_j$). Therefore,

$$DIC = \sum_i (NDP_i \cdot dpp_i) + \sum_j \; (NDC_j \cdot dpc_j) + (NDM_j \cdot dpm_j) \tag{20.34}$$

*DDC*, destructive disassembly cost, is calculated by multiplying the total amount of destructive disassembly components type *j* ($NDDC_j$) by its corresponding unit destructive disassembly cost ($ddc_j$). Therefore,

$$DDC = \sum_j (NDDC_j \cdot ddc_j) \tag{20.35}$$

*NDC*, nondestructive disassembly cost, is calculated by multiplying the total number of nondestructive disassembly components type *j* ($NNDC_j$) by its corresponding unit nondestructive disassembly cost ($ndc_j$). Therefore,

$$NDC = \sum_j (NNDC_j \cdot ndc_j) \tag{20.36}$$

*STC*, storage cost, is calculated by multiplying the total number of stored components type *j* ($NST_j$) by its corresponding unit holding cost ($hc_j$). Therefore,

$$STC = \sum_j (NST_j \cdot hc_j) \tag{20.37}$$

*REC*, cost of recycling process, is calculated by multiplying the total amount of materials recycled in plant ($RCI_j$), out plant ($RCO_j$), by their corresponding unit recycling cost for in-plant ($irc_j$) and out-plant ($orc_j$) processes. Therefore,

$$REC = \sum_j \; (RCI_j \cdot irc_j) + (RCO_j \cdot orc_j) \tag{20.38}$$

#### *20.6.1.3 The Constraints*

##### *20.6.1.3.1 Disassembly Process*

The total number of product type *i* to be disassembled ($TPD_i$) is equal to the total number of take-back EOL product type *i* ($TPT_i$) multiplied by the stochastic good condition percentage of product type *i* ($SPG_i$). Therefore,

$$TPD_i = TPT_i \cdot SPG_i \tag{20.39}$$

The total number of disassembled components type *j* ($TCD_j$) is equal to the sum of the total disassembled products type *i* ($TPD_i$) multiplied by its multiplicity of component type *j* ($M_{ij}$), for all product types. Therefore,

$$TCD_j = \sum_i (TPD_i \cdot M_{ij}) \tag{20.40}$$

The total number of nondestructive disassembly components ($TCND_j$) has to be no more than the sum of the multiplication of the total disassembled products type *i* ($TPD_i$), its corresponding multiplicity of component type *j* ($M_{ij}$) and nondestructive disassembly yields of component type *j* ($DY_{ij}$) calculated from the heuristic approach, for all product types. Therefore,

$$TCND_j \leq \sum_i (TPD_i \cdot M_{ij} \cdot DY_{ij}) \tag{20.41}$$

The total amount of destructive disassembly components type *j* ($TCDD_j$) is equal to the subtraction of nondestructive disassembly components type *j* ($TCND_j$) from the total number of disassembly components type *j* ($TCD_j$). Therefore,

$$TCDD_j = TCD_j - TCND_j \tag{20.42}$$

*20.6.1.3.2 Reuse Process*

The number of components type *j* sent to reuse process ($NRPC_j$) cannot exceed the number of nondestructive disassembly of components type *j* ($TCND_j$). Therefore,

$$NRPC_j \;''\; TCND_j \tag{20.43}$$

The number of good-to-reuse components type *j* ($GRC_j$) has to be equal to the multiplication of the number of components type *j* sent to reuse process ($NRPC_j$) and its stochastic reusable percentage ($SRC_j$). Therefore,

$$GRC_j = NRPC_j \cdot SRC_j \tag{20.44}$$

The number of bad-to-reuse components type *j* ($BRC_j$), which cannot be reused and will be used in the recycling process, has to be equal to the number of components type *j* sent to reuse process ($NRPC_j$) subtracted by the number of good-to-reuse component type *j* ($GRC_j$). Therefore,

$$BRC_j = NRPC_j - GRC_j \tag{20.45}$$

The demand of reuse component type *j* ($D_j$) has to be equal to the sum of good-to-reuse components type *j* ($GRC_j$) and the procured components type *j* from outside supplier ($OSPC_j$). Therefore,

$$D_j = GRC_j + OSPC_j \tag{20.46}$$

The outside procurement is only needed when the demand cannot be fulfilled. Therefore, the number of procured components type *j* ($OSPC_j$) is equal to the maximum value between the subtraction of the number of reusable component type *j* ($GRC_j$) from the demand of reuse component type *j* ($D_j$), and zero. Therefore,

$$OSPC_j = Max\{(D_j - GRC_j), 0\} \tag{20.47}$$

### *20.6.1.3.3 Recycling Process*

In general, all the materials of the components cannot be recovered in recycling process. Hence, the total number of components type *j* to be recycled ($NCRE_j$) is equal to the recycle demand of components type *j* ($REDC_j$) divided by its corresponding stochastic recyclable percentage ($SRP_j$). Therefore,

$$NCRE_j = REDC_j/SRP_j \tag{20.48}$$

Also, the total number of components type *j* to be recycled ($NCRE_j$) cannot exceed the sum of the number of bad-to-reuse components type *j* ($BRC_j$) and the total number of destructive disassembly components type *j* ($TCDD_j$). Therefore,

$$NCRE_j \le BRC_j + TCDD_j \tag{20.49}$$

The sum of the total number of components type *j* recycled in-plant ($RCI_j$) and out-plant ($RCO_j$) has to be equal to the total number of components type *j* to be recycled ($NCRE_j$). Therefore,

$$NCRE_j = RCI_j + RCO_j \tag{20.50}$$

The number of in-plant recycled components type *j* ($RCI_j$) cannot exceed the in-plant capacity for components type *j* ($CIP_j$). Therefore,

$$RCI_j \;''\; CIP_j \tag{20.51}$$

The number of components type *j* that exceeds the recycle demands will be sent to disposal. Hence, the number of disposed components type *j* from the recycle process ($DREC_j$) is calculated as a maximum value between the subtraction of the total number of components type *j* to be recycled ($NCRE_j$) from the sum of the number of bad-to-reuse components type *j* ($BRC_j$) and the total number of destructive disassembly components type *j* ($TCDD_j$), and zero. Therefore,

$$DREC_j = Max\{[(BRC_j - TCDD_j) - NCRE_j], 0\} \tag{20.52}$$

The total weight of the recycling material type *j* ($WRM_j$) is equal to the multiplication of the number of recycled components type *j* ($NCRE_j$), weight of components type *j* ($W_j$) and their stochastic recyclable percentage ($SRP_j$). Therefore,

$$WRM_j = NCRE_j \cdot W_j \cdot SRP_j \tag{20.53}$$

#### *20.6.1.3.4 Storage Process*

The total number of stored components type *j* ($NSC_j$) is equal to the subtraction of the number of components type *j* sent to reuse process ($NRPC_j$) from the total number of nondestructive disassembly components type *j* ($TCND_j$). Therefore,

$$NSC_j = TCND_j - NRPC_j \tag{20.54}$$

The total number of stored components type *j* ($NSC_j$) cannot exceed the available storage capacity for components type *j* ($ASC_j$). Therefore,

$$NSC_j \;''\; ASC_j \tag{20.55}$$

The number of components type *j* that exceeds the storage capacity ($ESC_j$) will be sent to disposal. It is calculated as a maximum value between the subtraction of the available storage capacity for components type *j* ($ASC_j$) from the total number of stored components type *j* ($NSC_j$), and zero. Therefore,

$$ESC_j = Max\{(NSC_j - ASC_j), 0\} \tag{20.56}$$

#### *20.6.1.3.5 Disposal Process*

The total number of disposal products type *i* ($NDP_i$) is equal to the subtraction of the number of products type *i* to be disassembled ($TPD_i$) from the total number of takeback EOL products type *i* ($TPT_i$). Therefore,

$$NDP_i = TPT_i - TPD_i \tag{20.57}$$

The total number of disposing components type *j* ($NDC_j$) is equal to the sum of the number of disposal components type *j* from the recycle process ($DREC_j$) and the number of components type *j* that exceed the storage capacity ($ESC_j$). Therefore,

$$NDC_j = DREC_j + ESC_j \tag{20.58}$$

The total number of disposing material type $j$ ($NDM_j$) is equal to the multiplication of the amount of components type j to be recycled in plant ($RCI_j$), weight of material type $j$ ($WM_j$), and nonrecyclable percentage ($1-SRP_j$). Therefore,

$$NDM_j = RCI_j \cdot WM_j \cdot (1 - SRP_j) \tag{20.59}$$

#### 20.6.1.4 The Goal Programming Model

The GP model can now be written as follows:
Find ($TPT_i$, $TCND_j$, $TCDD_j$, $NRPC_j$, $NCRE_j$, $NSC_j$, $NDC_j$) so as to

$$\text{Lexicographically minimize } u = \{(d_1^-), (d_2^+), (d_3^+), (d_4^+)\} \tag{20.60}$$

where $\{d_k^-, d_k^+\}$ are defined in Equation 20.24 through Equation 20.27 (the terms of which are explained in Equation 20.28 through Equation 20.38), subject to constraints defined in Equation 20.39 through Equation 20.59 and all variables nonnegative and in addition, $TPT_j$, $TPD_j$, $TCND_j$, $NRPC_j$ and $GRC_j$ as integers.

#### 20.6.1.5 Procedure to Solve the GP Model

The following steps are used to solve the GP model:

*Step 1.* Read in all the relevant data. Set the first goal as current goal.

*Step 2.* Obtain a linear programming (LP) solution with the current goal as the objective function.

*Step 3.* If the current goal is the last goal, set it equal to the LP objective function value found in Step 2. STOP. Otherwise, go to Step 4.

*Step 4.* If the current goal is achieved or overachieved, set it equal to its aspiration level and add this to the constraint set. Go to Step 2. Otherwise, if the value of the current goal is underachieved, set the aspiration level of the current goal equal to the LP objective function value found in Step 2 and add this to the constraint set. Go to Step 5.

*Step 5.* Set the next goal of importance as the current goal. Go to Step 2.

### 20.6.2 Heuristic Procedures

The estimation of component yield from EOL products is very difficult due to high level of variability associated with the condition of EOL products.

In order to help predict and transform stochastic disassembly yields into deterministic equivalents, Inderfurth and Langella (2006) proposed two heuristic procedures:

- One-to-one heuristic approach
- One-to-many heuristic approach

In this chapter, we use one-to-one heuristic approach. That is why this section explains only this heuristic. Interested readers can find information on the one-to-many heuristic in Inderfurth and Langella (2006).

In the one-to-one heuristic approach, a product (core) with multiple components is decomposed into a series of single core–single component equivalents (see Figure 20.8). In order to achieve this, the core cost of product *i* is split and the core cost of component *j* associated with product *i* is estimated in proportion to the procurement costs of the components. This can be represented mathematically as

$$c_{ij}^{s} = (ctb_i + cse_i) \cdot \left. cpc_j \middle/ \sum_j cpc_j \right. \tag{20.61}$$

where $ctb_i$ is the takeback cost of product *i*, $cse_i$ is the separation cost, $c_{ij}^{s}$ is the core cost of component *j* attributed to product *i*, and $cpc_j$ is the procurement cost of component *j*.

We can apply this formula to the product given in Figure 20.8. If the core cost ($ctb_i + cse_i$) for this product is \$18, and procurement costs of components A, B, C, and D are \$6, \$8, \$10 and \$12, respectively, then the core cost of each component can be calculated as follows:

$$c_{1A}^{s} = 18 \cdot (6/36) = \$3$$

$$c_{1B}^{s} = 18 \cdot (8/36) = \$4$$

$$c_{1C}^{s} = 18 \cdot (10/36) = \$5$$

$$c_{1D}^{s} = 18 \cdot (12/36) = \$6$$

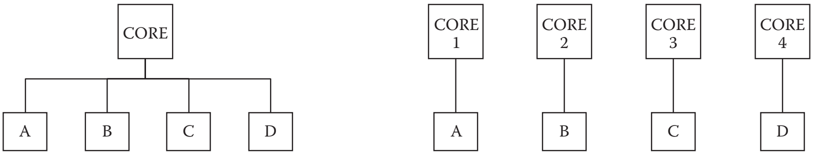

**FIGURE 20.8**
Splitting a product into one-to-one relation.

For uniformly distributed yield, the following closed-loop formulation for $\gamma$ (deterministic equivalent) was presented in Inderfurth and Langella (2006) as follows:

$$\gamma = \sqrt{\frac{cpc \cdot (SDY^{-})^2 + cdc \cdot (SDY^{+})^2 + 2 \cdot c^s \cdot (SDY^{+} - SDY^{-})}{cpc + cdc}} \tag{20.62}$$

where $SDY^{-}$ is the lower bound for yield realization, and $SDY^{+}$ is the upper bound for yield realization.

### 20.6.3 Numerical Example

In this section, a case study involving four EOL product types is considered. Figure 20.9 presents the bill of materials of these products. The input data required for the implementation of the preemptive goal programming process is provided in Table 20.12.

In addition to the data presented in Table 20.12, the following data is used in the case example. Product takeback cost ($tbc_i$) = {15, 18, 16, 20}, product disposal cost ($dpp_i$) = {3.5, 3.5, 3.5, 3.5}, stochastic percentage of good products ($SPG_i$) = {.92, .90, .93, .90} for product $i$, $I$= 1,2,3 and 4, in-plant recycling cost ($cir_j$) = 1.5, out-plant recycling cost ($cor_j$) = 2, in-plant capacity ($IPC_j$) = 500, available storage space ($ASC_j$) = 300 for all components $j$, $SDY^{+}$ = 0.95,

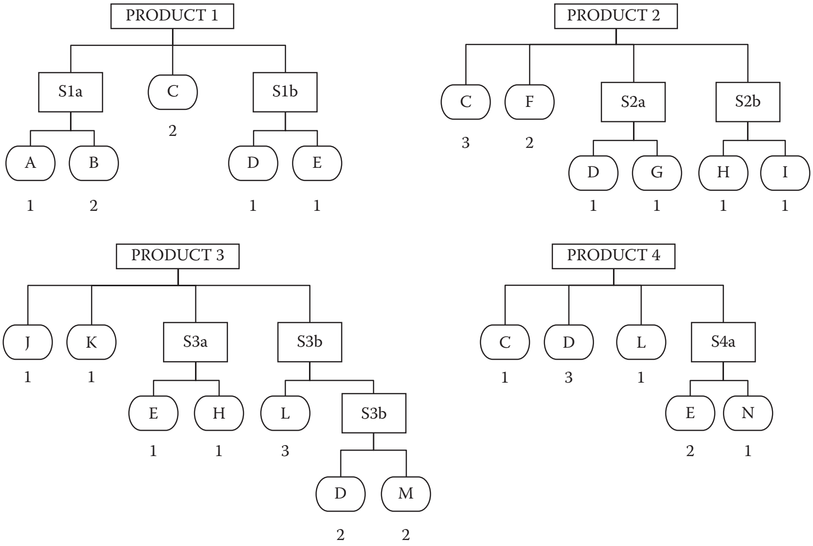

**FIGURE 20.9**
Bill of materials of products considered in case study.

**TABLE 20.12**

Input Data for the Case Study

| Component | Price of Component | Price of Material | Demand for Reuse Compo. | Demand for Recycle Mat. | Unit Holding Cost | Store Value | Dest. Diss. Cost | Non-Dest. Diss. Cost | Disposing Cost | Material Disposing Cost | Outside Procurement Cost | Stochastic Reusable Percentage | Stochastic Recyclable Percentage | Weight of Comp. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A | 10 | 5 | 350 | 220 | 0.40 | 9 | 0.40 | 0.60 | 0.7 | 0.5 | 10 | 0.80 | 0.75 | 1.4 |
| B | 12 | 8 | 450 | 260 | 0.45 | 10 | 0.30 | 0.50 | 0.5 | 0.3 | 12 | 0.75 | 0.70 | 1.2 |
| C | 8 | 4 | 330 | 200 | 0.30 | 7 | 0.25 | 0.65 | 0.8 | 0.6 | 8 | 0.85 | 0.85 | 2 |
| D | 14 | 7 | 380 | 250 | 0.55 | 13 | 0.40 | 0.70 | 0.9 | 0.7 | 14 | 0.75 | 0.95 | 0.8 |
| E | 13 | 8 | 300 | 200 | 0.5 | 12 | 0.25 | 0.50 | 0.6 | 0.4 | 13 | 0.90 | 0.90 | 1.5 |
| F | 11 | 7 | 280 | 180 | 0.60 | 10 | 0.35 | 0.55 | 0.5 | 0.3 | 11 | 0.95 | 0.75 | 1 |
| G | 10 | 6 | 420 | 260 | 0.45 | 9 | 0.40 | 0.65 | 0.5 | 0.3 | 10 | 0.80 | 0.70 | 1.3 |
| H | 9 | 5 | 350 | 230 | 0.55 | 8 | 0.45 | 0.70 | 0.7 | 0.5 | 9 | 0.85 | 0.95 | 1.7 |
| I | 10 | 4 | 380 | 240 | 0.5 | 9 | 0.50 | 0.65 | 0.6 | 0.4 | 10 | 0.75 | 0.85 | 1.5 |
| J | 12 | 6 | 250 | 160 | 0.35 | 10 | 0.55 | 0.55 | 0.4 | 0.2 | 12 | 0.85 | 0.75 | 1 |
| K | 13 | 9 | 400 | 250 | 0.65 | 11 | 0.30 | 0.50 | 0.5 | 0.3 | 13 | 0.90 | 0.90 | 2 |
| L | 11 | 7 | 480 | 300 | 0.35 | 10 | 0.55 | 0.75 | 0.4 | 0.2 | 11 | 0.95 | 0.85 | 1 |
| M | 8 | 3 | 330 | 210 | 0.40 | 2 | 0.45 | 0.70 | 0.6 | 0.4 | 8 | 0.85 | 0.95 | 1.2 |
| N | 9 | 4 | 360 | 220 | 0.45 | 8 | 0.40 | 0.60 | 0.5 | 0.3 | 9 | 0.75 | 0.70 | 1.1 |

$SDY^{-} = 0.45$, aspiration levels for total profit, procurement cost, take-back cost, and disposing cost are 38000, 11000, 31000, and 4400, respectively.

We used one-to-one heuristic to calculate the deterministic yield equivalents for the components of each product. The results are given in Table 20.13.

We can explain the calculation of deterministic yield for component D in product 2 as follows:

$$cse_2 = 3\cdot 0.65 + 2\cdot 0.55 + 1\cdot 0.7 + 1\cdot 0.65 + 1\cdot 0.7 + 1\cdot 0.65 = 5.75$$

$$ctb_2 = 18$$

$$c_{2D}^{s} = (18 + 5.75)\cdot(14/(3\cdot 8 + 2\cdot 11 + 1\cdot 14 + 1\cdot 10 + 1\cdot 9 + 1\cdot 10))$$

$$Y = \sqrt{\frac{14\cdot(0.45)^2 + 0.9\cdot(0.95)^2 + 2\cdot 3.736\cdot(0.95 - 0.45)}{14 + 0.9}} = 0.704$$

Having all the required input data, we solved the preemptive goal programming model for the case study. The results can be seen in Tables 20.14, 20.15, and 20.16.

## 20.7 Ergonomics (MOST)

Kroll (1996) developed a work-measurement analysis method for disassembly tasks. This method uses a spreadsheet-like evaluation chart developed based on a catalog of task difficulty scores. In this section, we illustrate the implementation of this method by considering the disassembly of a cellphone. The steps of the method can be summarized as follows:

- Standard disassembly activities or tasks are determined.
- For each activity or task, a MOST (see Section 2.12) sequence model is defined. While defining this model, four sources of difficulty associated with disassembly tasks are considered (viz., accessibility, positioning, force, and base time).
- A difficulty scale of 1 to 10 is created. In this scale, 1 is assigned to disassembly task of picking up and removing a light, easily grasped part. A difficulty score of 1 corresponds to a component time of zero. Force component of a common unscrew operation is assigned a difficulty score of 10, which corresponds to a time block of 260 TMU (TMU is a time measurement unit defined to be 0.00001 h = 0.036 seconds). The following formula is used to calculate difficulty scores for component times:

$$\text{Difficulty Score} = 1 + \frac{9\cdot(\text{Component time in TMU})}{260} \tag{20.63}$$

**TABLE 20.13**

Deterministic Yield Equivalents from One-to-One Heuristic Approach

| Product 1 | | Product 2 | | Product 3 | | Product 4 | |
|---|---|---|---|---|---|---|---|
| **Component** | **Deterministic Yield** | **Component** | **Deterministic Yield** | **Component** | **Deterministic Yield** | **Component** | **Deterministic Yield** |
| A | 0.693 | C | 0.713 | D | 0.649 | C | 0.710 |
| B | 0.685 | D | 0.704 | E | 0.643 | D | 0.700 |
| C | 0.701 | F | 0.699 | H | 0.654 | E | 0.688 |
| D | 0.691 | G | 0.700 | J | 0.638 | L | 0.692 |
| E | 0.686 | H | 0.708 | K | 0.640 | N | 0.698 |
| | | I | 0.703 | L | 0.639 | | |
| | | | | M | 0.653 | | |

**TABLE 20.14**

Values of Several Outputs at Different Stages of the PGP Process

| Goals | Aspiration Level | 1st Run | Goal 1 | Goal 2 | Goal 3 | Goal 4 |
|---|---|---|---|---|---|---|
| Total profit | ≥36000 | 36210.13 | 36000.62 | 36000.07 | 36000.00 | 36000.00 |
| Procurement cost | ≤14000 | 18978.00 | 13820.00 | 13984.00 | 13984.00 | 13984.00 |
| EOL product takeback cost | ≤30000 | 25305.00 | 29155.00 | 28780.00 | 28780.00 | 28780.00 |
| Disposing cost | ≤4300 | 3384.725 | 4363.925 | 4278.025 | 4277.983 | 4277.983 |
| **Other important Variables** | | | | | | |
| Components sale revenue (RCS) | | 54350.00 | 54350.00 | 54350.00 | 54350.00 | 54350.00 |
| Materials sale revenue (RMS) | | 21148.85 | 21148.85 | 21148.85 | 21148.85 | 21148.85 |
| Stored component value (SVL) | | 20146.00 | 20567.00 | 20192.00 | 20192.00 | 20192.00 |
| Storage cost (cst) | | 952.0000 | 1020.600 | 1004.050 | 1004.050 | 1004.050 |
| Disassembly cost (CDD+CND) | | 5980 | 6870.7 | 6809.7 | 6809.7 | 6809.7 |
| Recycling cost (CRE) | | 4835.000 | 4835.000 | 4835.000 | 4835.117 | 4835.117 |

**TABLE 20.15**

Optimum Takeback Amounts for Each Product Type

| Product | Takeback amount |
|---|---|
| 1 | 500 |
| 2 | 460 |
| 3 | 500 |
| 4 | 250 |

Table 20.17 presents parameter allocations, component times (in TMU), and difficulty scores for each manual unscrew of a single screw or nut classification. In this table, parameter allocation for the force component of the first category is $L_6$. Component time in TMU is calculated as 6*10 = 60 for this category. Using the equation 20.63, the difficulty score can be calculated as follows:

$$\text{Difficulty Score} = 1 + \frac{9 \cdot 60}{260} = 3.08 \approx 3$$

**TABLE 20.16**

Number of Components Allocated to Disassembly, Reuse, Outside Procurement, Recycling, Storing, and Disposal Processes

| Component | Nondest. Disassembly | Destructive Disassembly | Reuse | Outside Procurement | Recycle | Store | Dispose |
|---|---|---|---|---|---|---|---|
| A | 300 | 160 | 300 | 110 | 220 | 0 | 0 |
| B | 630 | 290 | 400 | 150 | 260 | 230 | 130 |
| C | 680 | 1707 | 380 | 7 | 200 | 300 | 1564 |
| D | 804 | 1675 | 504 | 2 | 250 | 300 | 1551 |
| E | 630 | 745 | 330 | 3 | 200 | 300 | 578 |
| F | 578 | 250 | 280 | 14 | 180 | 298 | 84 |
| G | 192 | 222 | 190 | 268 | 260 | 2 | 0 |
| H | 597 | 282 | 400 | 10 | 230 | 197 | 112 |
| I | 232 | 182 | 232 | 206 | 240 | 0 | 0 |
| J | 296 | 169 | 280 | 12 | 160 | 16 | 51 |
| K | 238 | 227 | 230 | 193 | 250 | 8 | 0 |
| L | 800 | 820 | 500 | 5 | 300 | 300 | 545 |
| M | 607 | 323 | 380 | 7 | 210 | 227 | 170 |
| N | 6 | 219 | 4 | 357 | 220 | 2 | 0 |

**TABLE 20.17**

Parameter Allocations, Component Times (in TMU), and Difficulty Scores for Each Manual Unscrew of a Single Screw or Nut Classification

| **Category** | **Parameter Allocations** | | | | **Component Times in TMU** | | | | **Difficulty Scores** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Accessibility** | **Positioning** | **Force** | **Base time** | **Accessibility** | **Positioning** | **Force** | **Base Time** | **Accessibility** | **Positioning** | **Force** | **Base Time** |
| Clear fastener, light resistance | None | $P_3$ | $L_6$ | $A_1$, $L_{16,}$ $A_1$, $G_1$ | 0 | 30 | 60 | 190 | 1 | 2 | 3 | 8 |
| Clear fastener, heavy resistance | None | $P_3$ | $L_{42-16}$ | A1, L16, A1, G1 | 0 | 30 | 260 | 190 | 1 | 2 | 10 | 8 |
| Obstructed fastener, light resistance | $P_{6-3}$ | $P_3$ | $L_6$ | $A_1$, $L_{16,}$ $A_1$, $G_1$ | 0 | 30 | 60 | 190 | 2 | 2 | 3 | 8 |
| Obstructed fastener, heavy resistance | $P_{6-3}$ | $P_3$ | $L_{42-16}$ | $A_1$, $L_{16,}$ $A_1$, $G_1$ | 30 | 30 | 260 | 190 | 2 | 2 | 10 | 8 |

The completed evaluation chart is presented in Figure 20.10. In this chart, part number, part name, quantity, task type, number of task repetitions, and required tool are presented in columns 1 through 6. The difficulty scores in five categories (viz., accessibility, positioning, force, base time, and special) for each part are entered in the following five columns. The values in column 12 are obtained by summing the scores for the five difficulty categories for each part. These values represent the difficulty associated with one repetition of a particular task. Total score of a task considering all repetitions (column 13) is determined by multiplying the value in column 12 by the value in column 5. Comments about a task are written in column 14. Columns 15 and 16 present the number of tool and hand manipulations associated with a task, respectively. The estimated disassembly time presented in column 17 can be calculated using the following equation:

$$\begin{aligned}\text{Disassembly Time} &= (\text{Column 13} - 5 \cdot \text{Column 5}) \cdot 1.04 \\ &\quad + (\text{Number of tool and hand manipulations}) \cdot 0.9 \qquad (20.64)\end{aligned}$$

For instance, estimated disassembly time for part number 3 is calculated as follows:

$$\text{Disassembly Time} = (30 - 5 \cdot 2) \cdot 1.04 + 2 \cdot 0.9 = 22.6 \text{ seconds.}$$

## 20.8 Numerical Examples (Disassembly Automation)

In this section, we present two numerical examples of disassembly automation adapted from Groover (2008).

### 20.8.1 Example 1

An automated disassembly line has 10 stations and operates with an ideal cycle time of 1 min. (i.e., $CT = 1$ min.). Probability of a station failure is $p = 0.006$, and average downtime when a breakdown occurs is 5 minutes. Determine

- The average production rate ($PR$)
- The line efficiency ($E$)

SOLUTION

- $F = np = 10(0.006) = 0.06$.

  $PT = 1 + 0.06(5.0) = 1 + 0.3 = 1.3$ min.

  $PR = 60/PT = 60/1.3 = 46.15$ units/hour.

**Disassembly Evaluation Chart**

**Product:** cell phone
**Prepared by:** M.A.I and S.M.G.

**Date:** September 2, 2010
**Sheet:** 1 of 1

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **Difficulty rating** | | | | | | | | | | |
| **Part No.** | **Part Name** | **Quantity** | **Task Type** | No. of Task Repetitions | **Required Tool** | **Accessibilty** | **Positioning** | **Force** | **Base Time** | **Special** | **Subtotal** | **Total** | **Comments** | **No. of Tool Manipulations** | **No. of Hand Manipulations** | **Estimated Time (s)** |
| 1 | Antenna | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 2 | Battery | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 3 | Type 1 bolt | 2 | Unscrew | 2 | Philips | 1 | 2 | 3 | 8 | 1 | 15 | 30 | Manual, clear, light resistance | 2 | | 22.6 |
| 4 | Antenna path | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 5 | Type 2 bolt | 4 | Unscrew | 4 | Philips | 1 | 2 | 3 | 8 | 1 | 15 | 60 | Manual, clear, light resistance | 2 | | 43.4 |
| 6 | Clip | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 7 | Rubber | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 8 | White cable | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 9 | Red/blue cable | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 10 | Metal top | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 11 | Orange cable | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 12 | Speaker | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 13 | Front cover | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |
| 14 | Back cover | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | | | 2 | 1.8 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 15 | Plastic screen | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | 2 | 1.8 |
| 16 | Keyboard | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | 2 | 1.8 |
| 17 | Circuit board | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | 2 | 1.8 |
| 18 | Microphone | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | 2 | 1.8 |
| 19 | LCD | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | 2 | 1.8 |
| 20 | Sub-keyboard | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | 2 | 1.8 |
| 21 | Internal IC board | 1 | Remove | 1 | Hand | 1 | 1 | 1 | 1 | 1 | 5 | 5 | 2 | 1.8 |
| | | | | | | | | | | | | | | Total = 100.2 |

**FIGURE 20.10**
Disassembly evaluation chart.

where

$F$: Expected frequency of line stops per cycle
$n$: Number of stations
$p$: Expected frequency of station stops per cycle
PT: Average production time per unit

- $E = CT/PT = 1/1.3 = 0.77$.

### 20.8.2 Example 2

An automated disassembly line with ten stations was designed to operate with an ideal production rate of forty parts per hour. Efficiency of the line is 0.50 due to station breakdowns. The cost of operating the line is \$80 per hour without considering the cost of materials. The line is active for 5,000 hours per year.

The management is considering a proposal for the setup of a computer monitoring system that will cost \$30,000 (installed) and will reduce downtime on the line by 40%. Assuming \$5 to be the value added per unit produced, will this new computer system pay for itself within one year of operation?

**SOLUTION**

$$CT = 60/CR = 60/40 = 1.5 \text{ min.}$$
$$PT = CT/E = 1.5/0.50 = 3 \text{ min.}$$
$$PR = 60/PT = 60/3 = 20 \text{ units/hour.}$$

**FOR THE CURRENT LINE**

Annual production quantity ($Q$) = 5000 ($PR$) = 5000(20) = 100,000 units/year.

Total revenue = \$5($Q$) = \$5(100,000) = \$500,000/year.

Cost to operate the line = \$80(5000) = \$400,000/year.

**FOR THE LINE WITH COMPUTER MONITORING SYSTEM:**

$CT = 1.5$ min. and $PT = 3$ min.

$$\underbrace{\overset{\substack{\text{Downtime}\\ \text{Frequency}\\ \uparrow}}{F}\cdot\overset{\substack{\text{Average}\\ \text{Downtime per}\\ \text{line stop}\\ \nearrow}}{D}}_{\substack{\text{Downtime}\\ \text{averaged on a}\\ \text{per cycle basis}}} = PT - CT$$

Since the new system reduces $F \cdot D$ by 40%, the new $F \cdot D$ can be calculated as follows:

$F \cdot D = (1 - 0.40)(3 - 1.5) = 0.60(1.5) = 0.9$ min.

$PT = 1.5 + 0.9 = 2.4$ min.

$PR = 60/2.4 = 25$ units/h.

Annual production quantity ($Q$) = 5000(25) = 125,000 units/year.

Total revenue = \$5.00 (125,000) = \$625,000/year.

Cost to operate the line will be same as in the current system if we neglect the increased cost of the new system.

Difference in total revenue = \$625,000 – \$500,000 = \$125,000. This amount is much higher than the \$30,000 investment. Hence, computer monitoring system should be installed.

## 20.9 Other Models

### 20.9.1 Scheduling

We can distinguish two types of disassembly scheduling problems: uncapacitated and capacitated. For the first case, an MRP-like algorithm is proposed by Gupta and Taleb (1994) considering the disassembly scheduling of a discrete, well-defined product structure. The quantity and timing of disassembly of a single product to fulfill the demand for its various parts is determined by this algorithm. Extending Gupta and Taleb (1994), Taleb et al. (1997), and Taleb and Gupta (1997) consider components/materials commonality and the disassembly of multiple product types. A two-phase heuristic algorithm is proposed by Lee and Xirouchakis (2004) based on the objective of minimizing various costs related with the disassembly process. An initial solution is determined in the first phase using Gupta and Taleb's (1994) algorithm. This initial solution is improved in the second phase using a backward move. Extending the reverse MRP algorithm of Gupta and Taleb (1994), Barba-Gutierrez et al. (2008) develop a methodology that allows lot sizing in reverse MRP. Kim et al. (2003) propose a heuristic algorithm based on the LP relaxation for the case of multiple product types with parts commonality with the aim of minimizing the sum of setup, disassembly operation, and inventory holding costs. Kim et al. (2006b) develop a two-phase heuristic by extending Kim et al.'s (2003) study. The first phase involves the construction of an initial solution using the LP relaxation heuristic suggested by Kim et al. (2003). The second phase improves the initial solution using DP. Three IP models are proposed by Lee et al. (2004) for the three cases of the uncapacitated disassembly scheduling problem (viz., a single product type without parts commonality and single and multiple product types with parts commonality). A branch-and-bound algorithm is proposed by Kim et al. (2009c) for the case of single-product type without parts commonality.

An optimization algorithm is proposed by Meacham et al. (1999) for the capacitated case by considering common components among products and limited inventory of products available for disassembly. An IP model is proposed by Lee et al. (2002) based on the minimization of the sum of the disassembly operation and inventory holding costs. However, the model requires excessive computation times to find optimal solutions for practical-sized problems. As an extension to Lee et al. (2002), Kim et al. (2006a) develop a Lagrangean heuristic to find an optimal solution for practical problems in a reasonable amount of time. The objective function considered in the study involves also disassembly setup costs. In Kim et al. (2006c), an optimal algorithm is developed considering single product type without parts commonality by minimizing the number of disassembled products. In the first step of this algorithm, Gupta and Taleb's (1994) algorithm is used to determine an initial solution. The second step involved a feasibility check for this initial solution. Any infeasible solution is modified in order to satisfy the capacity constraints.

In Stuart and Christina (2003), disassembly and bulk recycling scheduling rules are defined based on the product turnover in incoming staging space. In a follow-up study, Rios and Stuart (2004) consider product turnover together with the outgoing plastics demand. Both studies employ DES models to evaluate scheduling rules. Brander and Forsberg (2005) consider sequence-dependent setups while developing a cyclic lot-scheduling heuristic for disassembly processes.

### 20.9.2 Sequencing

A disassembly sequencing problem was solved using various graphical approaches. An AND/OR graph-based methodology is presented by Lambert (1997). Kaebernick et al. (2000) sort the components of a product into different levels based on their accessibility for disassembly to develop a cluster graph. In Torres et al. (2003), a partial nondestructive disassembly sequence of a product is established by developing an algorithm based on the product representation. Possible disassembly sequences for maintenance are generated by Li et al. (2006) using a disassembly constraint graph (DCG). The methodology proposed by Dong et al. (2006) allows for the automatic generation of disassembly sequences from a hierarchical attributed liaison graph.

Several case-based reasoning (CBR) applications for disassembly sequencing were presented by researchers. In Zeid et al. (1997), CBR is applied in order to develop a disassembly plan for a single product. Veerakamolmal and Gupta, (2002) extend Zeid et al. (1997) by automatically generating disassembly process plans for multiple products using a CBR approach. A knowledge base assisting users in indexing and retrieving disassembly sequences is developed by Pan and Zeid (2001).

Another popular method applied to disassembly sequencing problem is petri net (PN) modeling. A PN-based approach for the automatic generation of disassembly process plans for products with complex AND/OR precedence relationships is proposed by Moore et al. (1998) and Moore et al. (2001). Disassembly petri nets (DPNs) for the design and implementation of adaptive disassembly systems have been proposed in Zussman and Zhou (1999) and Zussman and Zhou (2000). Zha and Lim (2000) develop an expert PN model for the disassembly planning by integrating expert systems and ordinary PNs. Tang et al. (2001) employ PN models for workstation status, product disassembly sequences, and scheduling while developing an integrated disassembly planning and demanufacturing scheduling approach. Tiwari et al. (2001) determined an effective disassembly sequencing strategy by integrating cost-based indices with PNs. A PN-based heuristic approach for disassembly sequence generation is developed by Rai et al. (2002). Kumar et al. (2003) and Singh et al. (2003) propose an expert enhanced colored stochastic PN consisting of a knowledge base, graphic characteristics, and artificial intelligence in order to deal with the unmanageable complexity of normal PNs. A fuzzy reasoning PN is proposed by Gao et al. (2004) to deal with the uncertainty associated with the disassembly process. Considering the uncertainty associated with the human factors in disassembly planning, a fuzzy attributed PN to deal with this uncertainty is proposed by Tang et al. (2006). In Grochowski and Tang (2009), an expert system capable of determining the optimal disassembly action without human assistance is developed by integrating a DPN and a hybrid Bayesian network.

Mathematical programming techniques were also used for disassembly sequence generation. An algorithm based on straightforward LP is proposed by Lambert (1999) for the determination of optimal disassembly sequences. Considering sequence dependent costs and disassembly precedence graph representation, Lambert (2006) proposed a methodology based on the iterative use of binary integer linear programming (BILP). The same methodology is applied to the problems with AND/OR representation by Lambert (2007).

Many metaheuristics-based disassembly sequencing methodologies were presented due to combinatorial nature of the disassembly sequencing problem. Seo et al. (2001) consider both economic and environmental aspects while developing a GA-based heuristic algorithm to determine the optimal disassembly sequence. Li et al. (2005) develop an object-oriented intelligent disassembly sequence planner by integrating DCG and a GA. GA-based approaches for disassembly sequencing of EOL products are presented by Kongar and Gupta (2006b), Giudice and Fargione (2007), Duta et al. (2008a), and Hui et al. (2008). A scatter search-based methodology to deal with the optimum disassembly sequence problem for complex products with sequence-dependent disassembly costs is proposed by Gonzalez and Adenso-Diaz (2006). They assume that only one component can be released at each time. Chung and Peng (2006) consider batch disassembly and tool accessibility while generating a feasible selective disassembly plan by developing a GA. Shimizu et al. (2007) derive an optimal disassembly sequence by applying genetic programming as a resolution method. Reveliotis (2007) provides (near-) optimal disassembly sequences by presenting a reinforcement-learning-based approach. Tripathi et al. (2009) consider the uncertainty inherent in the quality of the returned products while presenting a fuzzy disassembly sequencing problem formulation. An Ant Colony Optimization (ACO)-based metaheuristic has been developed to determine the optimal disassembly sequence as well as the optimal depth of disassembly. A multiobjective TS algorithm is proposed by Kongar and Gupta (2009a) to generate near optimal/optimal disassembly sequences. A GA-based methodology of integrated assembly and disassembly sequencing is developed by Tseng et al. (2010).

Various heuristic procedures were proposed to solve the disassembly sequencing problem. In Gungor and Gupta (1997), different disassembly strategies are evaluated by developing a methodology. The near-optimal disassembly sequences are also determined by proposing a heuristic procedure. Addressing the uncertainty related difficulties in disassembly sequence planning, Gungor and Gupta (1998) present a methodology for disassembly sequence planning for products with defective parts in product recovery. A disassembly sequence and cost analysis study for electromechanical products during the design stage is presented by Kuo (2000). Four stages are distinguished for disassembly planning: geometric assembly representation, cut-vertex search analysis, disassembly precedence matrix analysis, and disassembly sequences and plan generation. Three types of disassembly cost are considered (viz., target disassembly cost, full disassembly cost, and optimal disassembly cost). In Gungor and Gupta (2001a), a branch-and-bound algorithm is used for disassembly sequence plan generation. Erdos et al. (2001) use a heuristic to decompose the problem by discovering the subassemblies within the product structure. Then, the optimal disassembly sequence is determined by using the shortest hyperpath calculation. An algorithm based on minimax regret criterion is proposed by Kang et al. (2003) to solve the disassembly sequencing problem with interval profit values in the objective function. Mascle and Balasoiu (2003) use wave propagation to develop an algorithm that can determine the disassembly sequence of a specific component of a product. The heuristic algorithm proposed by Lambert and Gupta (2008) detected "good enough" solutions for disassembly sequencing problems in case of sequence dependent costs. Both the heuristic algorithm and the iterative BILP method (Lambert, 2006) are applied to the disassembly precedence graph of a cell phone. A precedence-constrained asymmetric traveling salesman problem formulation together with a three phase iterative solution procedure are proposed by Sarin et al. (2006). Adenso-Diaz et al. (2008) solve a bi-criteria disassembly planning problem by developing a GRASP and path-relinking-based heuristic methodology.

In Hsin-Hao et al. (2000), a neural network is employed for disassembly sequence generation.

### 20.9.3 Line Balancing

The first examples of disassembly line balancing algorithms were presented by Gungor and Gupta (2001b) and Gungor and Gupta (2002). The disassembly line balancing problem in the presence of task failures (DLBP-F) is analyzed by Gungor and Gupta (2001b). They presented a disassembly line balancing algorithm which assigns tasks to workstations by minimizing the effect of the defective parts on the disassembly line. Disassembly line related complications and their effects are discussed by Gungor and Gupta (2002). They also modify the existing concepts of assembly line balancing in order to demonstrate the applicability of some important factors in disassembly to balance a paced disassembly line. The two-phase PNs and DES-based methodology proposed by Tang and Zhou (2006) consider line balance, different process flows, and meeting different order due dates in order to maximize system throughput and system revenue by dynamically configuring the disassembly system into many disassembly lines.

Disassembly line balancing problem was also solved using metaheuristics. In McGovern and Gupta (2006), an optimal or near-optimal solution is obtained by developing an ACO algorithm. Agrawal and Tiwari (2006) develop a collaborative ant colony algorithm for stochastic mixed-model U-shaped disassembly line balancing. McGovern and Gupta (2007b) obtain near-optimal solutions by employing several combinatorial optimization techniques (exhaustive search, GA and ACO metaheuristics, a greedy algorithm, and greedy/hill-climbing and greedy/2-optimal hybrid heuristics). They illustrate the implementation of the methodologies, measure performance and enable comparisons by developing a known, optimal, varying size dataset. A new formula for quantifying the level of balancing is developed by McGovern and Gupta (2007a). They also present a first-ever set of a priori instances to be used in the evaluation of any disassembly line balancing solution technique. Optimal or near-optimal solutions for DLBPs are obtained by developing a GA. A novel multiobjective ACO algorithm for DLBP is developed by Ding et al. (2010).

Several mathematical programming based methodologies were developed to solve the DLBP. An MIP formulation for profit maximization is provided by Altekin et al. (2008) for partial DLBP. The parts and tasks, the number of stations, and the cycle time are determined by the proposed model. Duta et al. (2008b) integrate integer quadratic programming and branch and cut algorithm to solve the problem of Disassembly Line Balancing in Real time (DLBP-R). Koc et al. (2009) check the feasibility of the precedence relations among the tasks while developing IP and DP formulations for DLBP by using an AND/OR graph.

### 20.9.4 DTO Systems

Several heuristics were developed for DTO systems under the assumption of deterministic disassembly yield. In Lambert and Gupta (2002), a method called *tree network model* is developed by modifying the disassembly graph method for a multiproduct demand driven disassembly system with commonality and multiplicity. Kongar and Gupta (2002) determine the best combination of multiple products to selectively disassemble to meet the demand for items and materials under a variety of physical, financial and environmental constraints, and goals by developing a single period integer GP model. Extending Kongar and Gupta (2002), Kongar and Gupta (2006a) employ fuzzy GP to model the fuzzy aspiration levels of various goals. In Langella (2007), a multiperiod heuristic is developed by considering holding costs and external procurement of items. Kongar and Gupta (2009b) propose a LPP-based solution methodology that can satisfy tangible or intangible financial, environmental, and performance related measures of DTO systems. Kongar and Gupta (2009a) develop a multi objective TS algorithm by considering multiple objective functions, viz. maximizing the total profit, maximizing the resale/recycling percentage, and minimizing the disposal percentage. In Gupta et al. (2010), a DTO problem is solved using a neural network.

The uncertainty associated with disassembly yield is considered in the second line of research. The effect of stochastic yields on the DTO system is investigated by developing two heuristic procedures (i.e., one-to-one, one-to-many) in Inderfurth and Langella (2006). Imtanavanich and Gupta (2006) deal with the stochastic elements of the DTO system by using the heuristic procedures developed by Inderfurth and Langella (2006). Then, the number of returned products that satisfy various goals is determined employing a GP procedure.

### 20.9.5 Ergonomics

Although disassembly tasks have a hands-on nature, the number of studies on the ergonomics of disassembly is very small. Kazmierczak et al. (2004) use several explorative methods such as site visits, interviews in order to analyze the current situation, and future perspectives for the ergonomics of car disassembly in Sweden. In Kazmierczak et al. (2005), disassembly work is analyzed considering time and physical work load requirements of constituent tasks. Kazmierczak et al. (2007) predict the performance of alternative system configurations in terms of productivity and ergonomics for a serial-flow car disassembly line by combining human and flow simulations. Tang et al. (2006) and Tang and Zhou (2008) define the effect of several human factors (e.g., disassembly time, quality of disassembled components, and labor cost) as membership functions in their fuzzy attributed PN models in order to address the uncertainty due to manual operations in disassembly. Bley et al. (2004) and Takata et al. (2001) investigate the human involvement in disassembly. Methods time measurement (MTM) is used by Desai and Mital (2005) to calculate the ease of disassembly scores for disassembly tasks.

### 20.9.6 Automation

Researchers studied different aspects of disassembly automation in recent years. Considering an integrated disassembly cell controlled by product accompanying information systems, Seliger et al. (2002) develop modular disassembly processes and tools. A semiautomated personal computer disassembly cell composed of several subsystems is presented by Torres et al. (2004). The recognition and localization of the product and of each of its components are provided by a computer vision subsystem. A modeling subsystem is employed for disassembly sequence and planning of the disassembly movements. Considering the disassembly of a video camera recorder and a PC, Weigl-Seitz et al. (2006) discuss the required equipment and suitable strategies for the automated disassembly. A disassembly line layout with the suitable software structures is also proposed. Kopacek and Kopacek (2006) discuss the robotized, semiautomatized, flexible disassembly cells for minidisks, PCBs, and mobile phones in industrial use. They also integrate disassembly families, mobile robots, and multiagent systems (MAS) in order to develop a modular approach. The advantages of emulation in control logic development and validation of new conceptual disassembly systems are investigated by Kim et al. (2009a). Kim et al. (2007) generate automatic control sequences for a partly automated system by developing an adaptive and modular control system that considers the availability of disassembly tools and the technological feasibility of disassembly processes and tools. Dynamic process planning procedure proposed by Kim et al. (2009b) generate available alternatives by a database-supported procedure and select the best suitable among them if a device or tool is not available. Santochi et al. (2002) discuss the software tools developed to optimize the disassembly process of discarded goods. Several solutions for the design of robotic disassembly cells are investigated by Duta and Filip (2008). An overview of layouts and modules of automated disassembly systems developed at various companies and research institutes is provided by Wiendahl et al. (2001).

## 20.10 Conclusions

In this chapter, various disassembly issues (viz., scheduling, sequencing, line balancing, DTO systems, ergonomics, and automation) were discussed. Several models and numerical examples were provided. An overview of other disassembly related models was presented in the previous section.

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# 21

# *Cleaning*

All the parts coming from the disassembly process are cleaned. The cleaning process involves washing away dirt and dust from the parts as well as degreasing, deoiling, derusting, and freeing the parts from old paint (Steinhilper, 1998). The following paragraphs explain some of the most commonly used cleaning methods (viz., thermal cleaning, solvent-based cleaning, biological cleaning, and abrasive cleaning) associated with remanufacturing (Bras, 2007).

In *thermal cleaning*, oil, grease, dirt, paint, adhesives, rust, and other contaminants are cleaned from metal surfaces using heat. Blasting must be subsequently used to remove the leftover ashes and surface oxides. Thermal cleaning cannot be used for plastic components, lighter metal components, or heat-treated components.

*Solvent-based cleaning* uses various solvents in the cleaning process. This cleaning technology can be detrimental to the environment, especially if the solvents cataloged by the Environmental Protection Agency (EPA) such as air-, water-, or land-hazardous contaminants are used in the process. Being the most benign chemical cleaning substances, aqueous-based solutions are commonly used in industry as an alternative to solvent-based cleaning. Washing, rinsing and drying are the main steps in a typical *aqueous cleaning process*. The temperature and/or chemistry of the water (viz., acidic, alkaline, neutral, and/or emulsion) and the mechanical form of application (e.g., immersion, spray, or both mechanisms) are the factors that affect the cleaning process. Aqueous cleaning is an environmentally friendly process since it does not use any substance hazardous to the environment. However, more water and more energy may be required. That is why a closed-loop system that recycles the cleaning solution and reduces the need for make-up water and detergent should be designed in order to have an efficient process.

In *biological cleaning*, oils and greases removed by the aqueous emulsions are consumed by bacteria in a bath. A sludge consisting of dead organisms is the only waste. Minimal downtime, and relatively small water, energy, and cleaning agent consumption are among the other benefits. High capital costs and safety concerns associated with the high-pressure components and potential increase in $CO_2$ levels in the worker area are the main disadvantages.

There is a need for *abrasive cleaning* following thermal or chemical cleaning processes. It removes rust and scale and improves surface finish and appearance. Mechanical automotive parts (viz., clutches, drive shafts, and engines) are usually cleaned using airless centrifugal steel-shot abrasion technologies while air-blasting with glass beads, aluminum oxide, and zinc oxide cleans electrical parts (viz., starters and alternators). During the cleaning process, some core components may be damaged due to the aggressiveness of the abrasive cleaning technologies. Another problem is that the heavy metal concentrations in the spent media will be very high. This may result in high disposal costs.

## References

Bras, B., Design for remanufacturing processes, in *Environmentally Conscious Mechanical Design*, M. Kutz, Ed. Hoboken, NJ: John Wiley & Sons, 2007, 283–318.

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# 22

# *Inspection*

Inspection of disassembled and cleaned parts is required to determine their reusability and reconditionability. According to Steinhilper (1998), there are two important aspects of inspection in remanufacturing:

- Specification of criteria and condition characteristics required for the determination of the condition of the components.
- Development and application of suitable and affordable testing equipment.

It must be noted that testing equipment used for the testing of new parts is generally used after reconditioning the disassembled parts. Hence, the first inspection following disassembly and cleaning is the visual inspection. Magnifying glasses, microscopes, high resolution cameras with electronic image processing are some of the devices that can be used for visual inspection (Steinhilper, 1998). Experienced personnel usually have information on the type of failures common to a particular product. They can also estimate time and cost to remanufacture the product (Bras, 2007).

Nondestructive inspection and testing methods are used to detect material failures if they are not at the surface. These methods can be classified into six major categories: visual, penetrating radiation, magnetic–electrical, mechanical vibration, thermal and chemical–electrochemical (Bras, 2007).

Embedded sensor technology (discussed in Chapter 14) can simplify the inspection process. The sensors embedded into products provide information on the condition and type of components before actually disassembling them. Besides important savings in inspection time and costs, use of sensor information provides important savings in disassembly, disposal, transportation, and backorder costs (see Section 14.3).

## 22.1 Sorting

When used products are received, they have to be sorted based on their conditions. During this initial sorting operation, some inspection methods can also be applied to the product. Workers' expertise and experience is also an important factor in a successful sortation of received used products. Besides sorting of used products, disassembled parts and subassemblies are also sorted following the disassembly of used products. Parts are generally classified into three categories (Steinhilper, 1998): reusable without reconditioning, reconditionable, and not reusable or reconditionable. The following part and product design characteristics should be considered to facilitate the sorting process (Bras, 2007):

- *Product and part variety should be reduced.* If there is less variety of parts that need to be sorted, the sorting process takes less time. A remanufacturer can achieve this objective by focusing on limited number of product and part types. In addition, part and used product sorting can be facilitated by standardizing fasteners, bearings, pulleys, etc.
- *Products should have distinctive features for easy recognition.* If different parts have to be used, they should be easily recognizable.
- *Readable labels, text, barcodes that do not wear out during the product's service life should be placed on products.* Radio-frequency identification (RFID) tags can also be used to facilitate sorting.

## 22.2 Numerical Analysis of Inspection

Various numerical models for inspection operations of manufacturing systems are presented by Groover (2008). In this section, we present some of these models considering the characteristics of remanufacturing systems.

### 22.2.1 Comparison of Final Inspection and Distributed Inspection

We can distinguish three inspection types in remanufacturing:

- Final inspection (i.e., one final inspection at the end of the remanufacturing operation sequence)
- Distributed inspection (i.e., inspection after each remanufacturing operation)
- Partially distributed inspection (i.e., inspections are located between groups of remanufacturing operations)

#### *22.2.1.1 Final Inspection*

In this inspection type, there is one inspection and sortation operation located at the end of the remanufacturing operation sequence. It is assumed that defective units are completely and accurately detected by the final inspection procedure. The cost associated with the inspection and sortation operation is added to the regular processing cost. Therefore, the following expression is used to calculate the cost associated with the processing and sorting of a batch ($C_b$):

$$C_b = N_0 \sum_{i=1}^{m} C_{pri} + N_0 C_{sf} = N_0 \sum_{i=1}^{m} C_{pri} + C_{sf} \tag{22.1}$$

where $N_0$ is the number of parts in the starting batch, $C_{pri}$ is the cost of processing at remanufacturing operation $i$, and $C_{sf}$ is the cost of the final inspection and sortation per remanufactured part. For the case of equal processing times, the following expression can be used to determine $C_b$:

$$C_b = N_0(mC_{pr} + C_{sf}) \tag{22.2}$$

#### 22.2.1.2 Distributed Inspection

In distributed inspection, there is an inspection and sortation operation following each remanufacturing operation. In this arrangement, no defective units are processed in subsequent remanufacturing operations and the processing costs associated with these units are saved. Considering the defect rate $q_i$ at each operation, we can express $C_b$ as follows:

$$\begin{aligned} C_b &= N_0(C_{pr1} + C_{s1}) + N_0(1-q_1)(C_{pr2} + C_{s2}) + N_0(1-q_1) \\ &(1-q_2)(C_{pr3} + C_{s3}) + \cdots + N_0 \prod_{i=1}^{m-1} (1-q_i)(C_{prn} + C_{sn}) \end{aligned} \tag{22.3}$$

where $C_{s1}$, $C_{s2}$, …, $C_{si}$,…, $C_{sn}$ are the costs of inspection and sortation at each station. If $q_i = q$, $C_{pri} = C_{pr}$ and $C_{si} = C_s$ for all $i$, then we can express $C_b$ as follows:

$$C_b = N_0(1 + (1-q) + (1-q)^2 + \cdots + (1-q)^{m-1})(C_{pr} + C_s) \tag{22.4}$$

#### 22.2.1.3 Partially Distributed Inspection

In partially distributed inspection, inspections are done between groups of processes. The total batch cost is somewhere between "final inspection" and "distributed inspection."

#### 22.2.1.4 Numerical Example

A particular part is remanufactured through eight operations. The batch size is 500 and each operation has a fraction defect rate of 0.02. Processing cost for each operation is \$0.5. The cost of the single final inspection and sortation procedure ($C_{sf}$) is \$1.6. The cost of each inspection and sortation operation in distributed inspection ($C_s$) is \$0.2.

i. Compare the total processing and inspection costs for final inspection and distributed inspection.
ii. Determine the batch cost if the eight operations are divided into groups of four and inspections are carried out after operations 4 and 8.

*SOLUTION*

i. $C_b = 500(8 * 0.5 + 1.6) = \$2800$

$$C_b = 500(1 + (0.98) + (0.98)^2 + \cdots + (0.98)^7)(0.5 + 0.2) = \$2612$$

ii. In this case, the defects produced in the first four operations are separated from the rest of the batch by carrying out inspection after operation 4. The reduced batch is processed through operations 5 and 8. Another inspection operation is carried out at operation 8. The expression for the calculation of batch cost can be written as follows:

$$C_b = N_0 \sum_{i=1}^{4} C_{pri} + C_{s4} + N_0 \prod_{i=1}^{4} (1 - q_i) \sum_{i=5}^{8} C_{pri} + C_{s8}$$

In this expression $C_{s4} = C_{s8} = 4(0.2) = 0.8$.

The expression for total batch cost can be simplified as follows due to equal $C_{pri}$ and $q$ values:

$$C_b = N_0(4C_{pr} + C_{s4}) + N_0(1 - q)^4(4C_{pr} + C_{s8})$$

Putting numerical values for the example, $C_b$ is calculated as follows:

$$C_b = 500(4 \cdot 0.5 + 0.8) + 500(1 - 0.02)^4 \left(4 \cdot 0.5 + 0.8\right) = \$\ \$2691$$

### 22.2.2 Inspection versus No Inspection

While deciding between 100% inspection, sampling, and no inspection, the costs associated with these alternatives must be considered. The total cost of

100% inspection per batch can be written as follows:

$$C_b(100\%\ \text{inspection}) = NC_s \tag{22.5}$$

where $C_b$ is batch cost, $N$ is the number of parts in the batch, and $C_s$ is the inspection and sortation cost per part. The total cost of "no inspection" is given as follows:

$$C_b(\text{no inspection}) = NqC_d \tag{22.6}$$

where $q$ is the fraction defect rate and $C_d$ is the damage cost per defective part. The total cost of "sampling inspection" can be written as follows:

$$C_b(\text{sampling}) = C_sN_s + (N - N_s)qC_dP_a + (N - N_s)C_s(1 - P_a) \tag{22.7}$$

where $N_s$ is the number of parts in the sample, $q$ is the fraction defect rate, and $P_a$ is the probability of accepting the batch based on the sample. This probability can be determined by using an operating characteristic (OC) curve (Montgomery, 2008) for a specific $q$ value.

An inspection decision can be taken by comparing the expected fraction defect rate with a critical level ($q_c$). We can express $q_c$ as follows:

$$q_c = \frac{C_s}{C_d} \tag{22.8}$$

If $q$ is less than $q_c$, then there is no need for inspection. If $q$ is greater than $q_c$, inspection and sortation is performed prior to subsequent processing.

### 22.2.2.1 Numerical Example

In a remanufacturing facility, a batch of 5,000 parts has been remanufactured. The management must decide between two inspection alternatives: 100% inspection and no inspection. Based on the remanufacturing history of the part, the fraction defect rate is approximately 0.04. Inspection cost per part is \$0.2. The damage cost for each defective unit in the batch will be \$8, if the batch is passed on for subsequent processing.

i. Calculate the batch cost for 100% inspection.
ii. Calculate the batch cost if no inspection is performed.
iii. Determine the critical fraction defect level.
iv. Suppose that sampling inspection is used for this system by taking fifty parts from the batch randomly. According to the OC curve for this sampling plan, the probability of accepting the batch is 90% for the given defect rate ($q = 0.04$). Determine the batch cost of sampling inspection.

*SOLUTION*

i. $C_b(100\%\ \text{inspection}) = 5000 \cdot 0.20 = \$\ 1000$

ii. $C_b(\text{no inspection}) = 5000 \cdot 0.04 \cdot 8 = \$\ 1600$

iii. $q_c = \dfrac{0.2}{8} = 0.025$

The calculated $q_c$ value is less than the anticipated defect rate in the batch ($q = 0.04$). That is why inspection is required.

iv.
$$C_b(\text{sampling}) = 0.20(50) + (5000 - 50)(0.04)(\$8)$$
$$(0.90) + (5000 - 50)(\$0.2)(1 - 0.90) = \$1535$$

## 22.3 Conclusions

In this chapter, inspection and sorting operations were discussed. After providing brief information on inspection and sorting, several numerical examples were provided for the numerical analysis of inspection operations in remanufacturing.

## References

Bras, B., Design for remanufacturing processes, in *Environmentally Conscious Mechanical Design*, M. Kutz, Ed. Hoboken, NJ: John Wiley & Sons, 2007, 283–318.

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# 23

# Reassembly

## 23.1 The Issue

The parts are reassembled into a remanufactured product using the same power tools and equipment used in the assembly of new parts (Steinhilper, 1998). Hence, the solution methodologies and heuristics developed for assembly lines can be used in the analysis of reassembly lines. In this chapter, we apply the assembly line balancing techniques presented in Section 2.9 to the reassembly of a remanufactured product.

## 23.2 Application of Line Balancing Heuristics to Reassembly Lines

Time and predecessor information for work elements associated with the reassembly of a remanufactured product is given in Table 23.1. Based on this information, we apply three line balancing heuristics (viz., largest candidate rule, ranked positional weight, and Kilbridge–Wester method) to balance this reassembly line in the following subsections.

### 23.2.1 Largest Candidate Rule

Work elements listed in descending order based on time can be seen in Table 23.2. Figure 23.1 presents the precedence diagram. Assuming a line efficiency of 0.95 and a production rate of 15 remanufactured products per hour, cycle time and minimum number of workstations can be determined as follows:

$$\text{Cycle Time} = \frac{60 \cdot 0.95}{15} = 3.8\text{minutes}$$

$$w^* = \text{Min. Integer} \geq \frac{13.8}{3.8} = 3.63 = 4\,\text{stations}$$

**TABLE 23.1**

Time and Predecessor Information for Work Elements

| Work element | $wet_k$ | Predecessors |
|---|---|---|
| 1 | 0.8 | — |
| 2 | 1.4 | — |
| 3 | 1.2 | — |
| 4 | 2.2 | 1 |
| 5 | 2.3 | 1,2 |
| 6 | 1.3 | 2 |
| 7 | 0.7 | 3 |
| 8 | 0.9 | 4,5 |
| 9 | 2.4 | 6,7 |
| 10 | 0.6 | 8,9 |

Application of largest candidate rule as presented in Table 23.3 results in a solution with 4 stations. The balance efficiency for this solution can be determined as follows:

$$\text{Balance efficiency} = \frac{13.8}{4 \cdot 3.7} = 0.93$$

**TABLE 23.2**

Arrangement of Work Elements Based on Time for Largest Candidate Rule

| Work element | $wet_k$ | Predecessors |
|---|---|---|
| 9 | 2.4 | 6,7 |
| 5 | 2.3 | 1,2 |
| 4 | 2.2 | 1 |
| 2 | 1.4 | — |
| 6 | 1.3 | 2 |
| 3 | 1.2 | — |
| 8 | 0.9 | 4,5 |
| 1 | 0.8 | — |
| 7 | 0.7 | 3 |
| 10 | 0.6 | 8,9 |

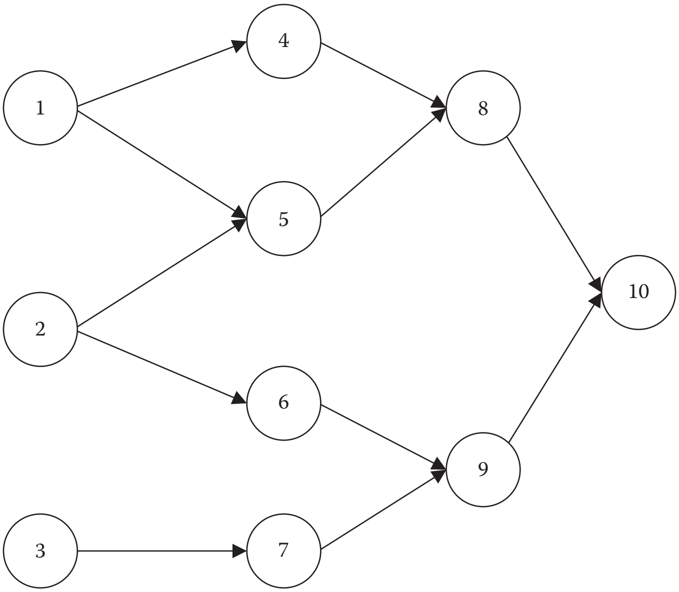

**FIGURE 23.1**
Precedence diagram for the example.

**TABLE 23.3**
Assignment of Work Elements to Stations According to Largest Candidate Rule

| Station | Work element | $wet_k$ | Station time |
|---|---|---|---|
| 1 | 2 | 1.4 | |
| | 5 | 2.3 | 3.7 |
| 2 | 6 | 1.3 | |
| | 3 | 1.2 | |
| | 1 | 0.8 | 3.3 |
| 3 | 4 | 2.2 | |
| | 8 | 0.9 | 3.1 |
| 4 | 7 | 0.7 | |
| | 9 | 2.4 | |
| | 10 | 0.6 | 3.7 |

**TABLE 23.4**

Arrangement of Work Elements Based on Ranked Positional Weight Value

| Work Element | RPW | $wet_k$ | Predecessors |
|---|---|---|---|
| 2 | 8.9 | 1.4 | — |
| 1 | 6.8 | 0.8 | — |
| 3 | 4.9 | 1.2 | — |
| 6 | 4.3 | 1.3 | 2 |
| 5 | 3.8 | 2.3 | 2 |
| 4 | 3.7 | 2.2 | 1 |
| 7 | 3.7 | 0.7 | 3 |
| 9 | 3 | 2.4 | 6,7 |
| 8 | 1.5 | 0.9 | 4,5 |
| 10 | 0.6 | 0.6 | 8,9 |

### 23.2.2 Ranked Positional Weight

Ranked positional weight (RPW) value is calculated for each element. As an example, RPW value for work element 2 can be calculated as follows:

$$RPW_2 = 1.4 + 2.3 + 1.3 + 0.9 + 2.4 + 0.6 = 8.9$$

Table 23.4 presents the work elements listed according to RPW value. Assignment of work elements to stations can be seen in Table 23.5.

**TABLE 23.5**

Assignment of Work Elements to Stations According to Ranked Positional Weight Method

| Station | Work Element | $wet_k$ | Station Time |
|---|---|---|---|
| 1 | 2 | 1.4 | |
| | 1 | 0.8 | |
| | 3 | 1.2 | 3.4 |
| 2 | 6 | 1.3 | |
| | 5 | 2.3 | 3.6 |
| 3 | 4 | 2.2 | |
| | 7 | 0.7 | |
| | 8 | 0.9 | 3.8 |
| 4 | 9 | 2.4 | |
| | 10 | 0.6 | 3 |

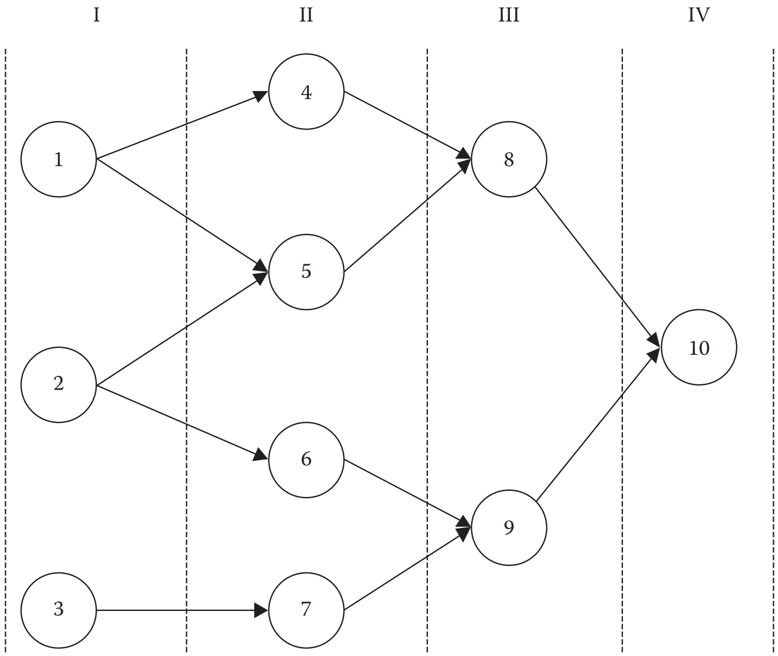

**FIGURE 23.2**
Arrangement of work elements into columns for the Kilbridge–Wester method.

The balance efficiency for the solution can be calculated as follows:

$$\text{Balance efficiency} = \frac{13.8}{4 \cdot 3.8} = 0.91$$

### 23.2.3 Kilbridge–Wester Method

Figure 23.2 presents the assignment of work elements to columns. Arrangement of work elements into columns according to the order of columns can be seen in Table 23.6. The Kilbridge–Wester solution is provided in Table 23.7.

The balance efficiency for the solution can be calculated as follows:

$$\text{Balance efficiency} = \frac{13.8}{4 \cdot 3.7} = 0.93$$

**TABLE 23.6**

Work Elements Listed Based on the Columns Presented in Figure 23.2

| Work element | Column | $wet_k$ | Predecessors |
|---|---|---|---|
| 2 | I | 1.4 | — |
| 3 | I | 1.2 | — |
| 1 | I | 0.8 | — |
| 5 | II | 2.3 | 2 |
| 4 | II | 2.2 | 1 |
| 6 | II | 1.3 | 2 |
| 7 | II | 0.7 | 3 |
| 9 | III | 2.4 | 6,7 |
| 8 | III | 0.9 | 4,5 |
| 10 | IV | 0.6 | 8,9 |

**TABLE 23.7**

Assignment of Work Elements to Stations According to Kilbridge–Wester Method

| Station | Work element | $wet_k$ | Station time |
|---|---|---|---|
| 1 | 2 | 1.4 | |
| | 3 | 1.2 | |
| | 1 | 0.8 | 3.4 |
| 2 | 5 | 2.3 | |
| | 6 | 1.3 | 3.6 |
| 3 | 4 | 2.2 | |
| | 7 | 0.7 | 3.7 |
| | 8 | 0.9 | |
| 4 | 9 | 2.4 | |
| | 10 | 0.6 | 3 |

## 23.3 Conclusions

In this chapter, reassembly in remanufacturing was discussed. Exploiting the similarity between assembly and reassembly lines, three assembly line balancing heuristics are applied to an example reassembly problem.

## Reference

Steinhilper, R., *Remanufacturing —The Ultimate Form of Recycling*. Stuttgart: Fraunhofer IRB Verlag, 1998.

# Part V

# Epilogue

# 24

# Conclusions

Consumers' ever growing appetite to acquire new products and their short courtship with them has kept the manufacturers busy expending our virgin resources at an alarming rate. This has led to serious depletion of these resources and given rise to increasing amounts of waste and pollution. The traditional way of manufacturing where we use only virgin materials to produce new products and dispose of the used products at the end of their lives, is unsustainable. Many countries and their governments have started to realize this problem and have imposed strict regulations, some of which require the manufacturers to take back their products when products reach the end of their lives. According to these regulations, the collected end-of-life (EOL) products must also be processed in an environmentally friendly manner. This has forced manufacturers to establish dedicated facilities for product recovery that involve the minimization of waste amounts sent to landfills by recovering parts and materials from EOL products via remanufacturing and recycling.

In remanufacturing, the collected EOL products are transported to a remanufacturing plant where they are disassembled into parts. Following the cleaning and inspection of disassembled parts, repair and replacement operations are performed to deal with defective and worn-out parts. Finally, all parts are reassembled into a remanufactured product that is expected to function like a new product. In addition to repair and replacement, some parts or modules may also be upgraded while remanufacturing a product.

Remanufacturing is the most environmentally friendly and profitable product recovery option since it has many advantages over other recovery options such as recycling, repairing, or refurbishing. In remanufacturing, the majority of labor, energy, and material values embedded in an EOL product are recovered because the disassembled parts are used as is in the remanufacturing process. On the other hand, in recycling, only the material is recovered, because the EOL products are simply shredded in a recycling facility. Remanufactured products provide superior performance due to replacement of worn-out parts and upgrading of some key parts. That is why many manufacturers are willing to give consumers the same warranty provisions as with the new products. Although replacement of some parts may occur during the repair or refurbishment option, there is no upgrading. Therefore, repaired or refurbished products may not provide a superior performance, and their warranty provisions are inferior to those of the remanufactured or new products.

While the history of remanufacturing dates back to the nineteenth century, it was used more systematically during World War II when many manufacturers diverted their regular product lines to military products. This led to an increase in the use of remanufactured products as countries experienced shortage of materials. Although, the importance of remanufacturing diminished somewhat during the decades that followed World War II, as the western countries flirted with the idea of throw away products, they soon started doubting its sustainability. As a consequence, there has been a renewed interest in remanufacturing in the past decade and an increase in the number of companies embracing remanufacturing has ensued because of its environmental and monetary advantages. Today, the size of the US remanufacturing industry is in the billions of dollars. Expansion of the remanufacturing industry has sparked research activities into the problems faced by remanufacturers. Academicians have started to address various design, planning, and processing issues encountered in remanufacturing systems. Among these issues, the following are the most prominent and common to all remanufacturing systems:

- Product design
- Reverse and closed-loop supply chain design
- Selection of used products
- Evaluation of remanufacturing facilities
- Forecasting
- Job sequencing
- Inventory management
- Production planning and control
- Capacity planning
- Pricing
- Control mechanisms
- Uncertainty management
- Product acquisition management
- Supplier evaluation
- Optimal supplier portfolio
- Selection of third-party reverse logistics providers
- Performance measurement
- Disassembly
- Cleaning
- Inspection
- Reassembly

In this book, we discussed these issues and provided examples of quantitative modeling methodologies to deal with them. The majority of these methodologies are based on popular industrial engineering and operations research techniques such as

- Taguchi loss functions
- Analytical hierarchy process
- TOPSIS
- Goal programming
- Fuzzy logic
- Linear physical programming
- House of quality
- Line-balancing techniques
- Simulation
- Design of experiments and orthogonal arrays
- Maynard operations sequence technique
- Linear integer programming
- Nonlinear programming
- Queuing theory
- Genetic algorithms

The issues addressed in this book can serve as foundations for researchers to build bodies of knowledge in these fast-growing areas of remanufacturing systems. Moreover, practitioners can utilize the models proposed in this book to analyze a particular remanufacturing issue.

**Manufacturing & Industrial Engineering**

# Remanufacturing Modeling and Analysis

New, Now, Next. Consumers' ever growing appetite to acquire new products and their short courtship with them has kept manufacturers busy not only expending resources at an alarming rate, but also depleting these resources and giving rise to waste and pollution at a correspondingly increasing and disturbing rate. Traditional manufacturing methods that use mainly virgin materials to produce new products and dispose of the used products at the end of their lives are quickly becoming unsustainable. In addition, regulations that require manufacturers to take back products and dispose of them responsibly have forced manufacturers to establish dedicated facilities for product recovery—systems that minimize waste and maximize remanufacturing and recycling.

**Remanufacturing Modeling and Analysis** explores the design, planning and processing issues encountered in remanufacturing systems and provides examples of quantitative modeling methodologies to deal with them. The book covers the history, industry size and potential, comparison with other end-of-life options, benefits, conditions, challenges, and steps in a typical process. It provides a brief overview of each of the industrial engineering and operations research techniques used in the book and explains the models developed to increase the remanufacturability of product designs. The book also discusses how increasingly stringent environmental regulations and decreasing natural resources influence manufacturers toward more environmentally conscious manufacturing and product recovery initiatives.

With easy-to-use mathematical or simulation modeling that demonstrates solutions for each remanufacturing issue, the book helps practitioners understand how a particular issue can be effectively modeled and how to choose the appropriate solution methodology. An in-depth look at quantitative analysis for remanufacturing systems, the book provides a foundation upon which to build a body of knowledge in this fast and growing area.

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