CREATING OPTIMAL SERVICE DELIVERY STRATEGY OF LONG-TERM SERVICE AGREEMENTS FROM RISK MANAGEMENT PERSPECTIVE

By

Chaipat Lawsirirat

A Thesis Submitted to the Graduate

Faculty of Rensselaer Polytechnic Institute

in Partial Fulfillment of the

Requirements for the Degree of

DOCTOR OF PHILOSOPHY

Major Subject: Decision Sciences and Engineering Systems

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Rensselaer Polytechnic Institute
Troy, New York

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The original of the complete thesis is on file
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CONTENTS

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المنارة للاستشارات
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المنارة للاستشارات
www.manaraa.com

www.manaraa.com

المنارة للاستشارات
www.manaraa.com

LIST OF TABLES

المنارة للاستشارات
www.manaraa.com

المنارة للاستشارات

www.manaraa.com

LIST OF FIGURES

للاستشارات المنارة

www.manaraa.com

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ABSTRACT

Long-term service agreements (LTSAs) for the maintenance of capital-intensive equipments, such as, gas turbines, medical equipments, aircraft and locomotive engines, are gaining wide acceptance. A typical LTSA contract spanning a period of 5-20 years makes a provider be responsible for fully maintaining customers' equipments. Effective management of LTSAs is very important, since these equipments are vital to the basic infrastructure and the economy of a country. This dissertation develops a rigorous framework for effectively managing the service delivery of LTSAs. Without a rigorous framework, the provider is exposed to extensive losses and endangers end-consumers' lives.

LTSAs combine several features of many problems, such as, service operations management, maintenance management, scheduling management, inventory management, and financial management. These problems are very well known and are studied extensively in the literature. However, these problems are often addressed separately. Our dissertation attempts to bridge these various disciplines through the perspective of risk management and assessment framework. The created integrated risk management framework focuses on strategic risks of the service delivery from the provider's perspective, since the provider plays the most critical role in creating the service. The framework allows us to develop an optimal service delivery strategy which provides the most reliable and top quality of service, meets the customer's requirements, reduces potential losses and risks with minimal costs while constantly looking towards improving profitability.

The framework begins by identifying potential sources of risks of the service delivery. After thorough identification of risks, we find a strategically optimal maintenance strategy for a multi-component product focusing only on product risks. Once we completely understand product risks, we integrate service risks into the framework where we attempt to develop an optimal service delivery strategy for LTSAs. We further enhance the framework by taking financial risks into account and develop an optimal buy and hold strategy which minimizes financial risks while

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fulfilling customer's requirements with minimal costs. Finally, we streamline decisions made at strategic business level to vigilantly develop a maintenance schedule for the equipments, a corresponding inventory plan, and a resource management so the costs are minimized.

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CHAPTER 1
Introduction

In today's services oriented economy, providing better services to customers is undeniably proving to be one of the main strategies even for organizations traditionally known to be manufacturers, such as, General Electric (GE) Company, United Technologies Corporation, etc. A particular service these traditional manufacturers are providing is service agreements bundled with their high cost, high technology, and long-lived products, e.g., locomotive engines, medical equipments, gas turbines, and aircraft engines. Such an agreement is intended to give customers assurances and/or ease of use of the products over an extended contract period running up to several decades. Long-term service agreements (LTSAs) are also provided by third party service companies, who do not necessarily be manufacturers of the products. We collectively call companies delivering this particular service in this dissertation as providers.

LTSAs offer a guarantee of the level of output generated from a product. For instance, GE sells aircraft engines bundled with long-term service agreements to United Airlines. United Airlines takes advantage of the service provided by the provider to improve its flight service quality. Hence, the provider sells not only its products but also the 'functionality' of the products. Bound by the contract, the provider is entitled to maintain the product in order to deliver the required functionality. Thus, the physical product (e.g., aircraft engine) only facilitates the service delivery. The provider fulfills its service delivery when the product functions at a specified level defined in the contract. The dissertation mainly focus on developing a framework to analyze the service part of the service delivery.

Practices as seen in Figure 1.1 are common in LTSAs. A customer purchases a product bundled with an LTSA from a provider. The provider guarantees the functionality of the product. The provider is responsible for maintaining and repairing the product for the customer over a specified period of time in exchange for a fee. The customer must accept constraints on how he can operate, allow real-

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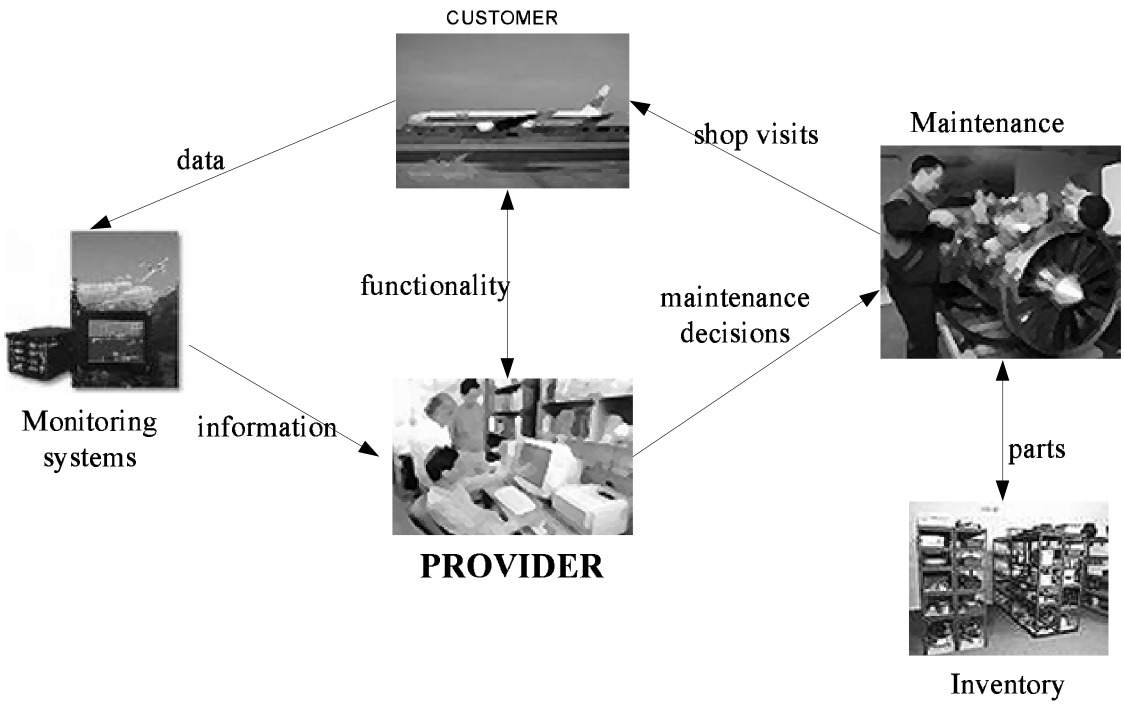

Figure 1.1: Infrastructure of LTSAs

time access to the product sensor data, and permit the provider to maintain the product. In this dissertation, some important strategic management problems for an efficient and effective delivery of long-term service agreements to customers from the provider's point of view are addressed.

1.1 Problem Background

Long-term service agreements are widely used and are gaining popularity among several manufacturers and/or third party service companies. These service agreements are either sold separately or bundled with products making the provider be responsible for delivering the products' functionality. Often the products under LTSAs are high cost, high technology, long-lived, vital to economy and provide critical infrastructure to the country. Moreover, the product's maintenance cost is almost comparable to the product's manufacturing cost. Products also need significant knowledge base and infrastructure to support the service delivery process.

The service agreement offers a well-crafted contractual specification for a spe-

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cific product with a specified price, leading to planned and/or unplanned maintenance of the product by the provider. The agreement usually runs for 5-20 years. The service generally includes all part replacements, repairs, equipment settings, and labor costs. The long-term service agreement is also often stated as a guarantee of products' output per unit time and the expectation of near-zero downtime due to failures under some specified conditions.

Many industries, e.g., airline business and car manufacturers, take advantage of LTSAs to reduce their maintenance cost, increase customer's satisfaction, and gain competitive edge over its rivals. It is estimated in Davies [122] that maintenance, repair and overhaul (MRO) for world wide airline business is worth $38 billion in 2005 compared to $34 billion in 2003. About 50% of MRO works for US commercial airlines are being outsourced to domestic and international contractors. By 2013, the North American MRO business is expected to grow in revenue by $21.5 billion [300]. The FAA expects that by 2010 70% of MRO will be outsourced to third parties [145].

United Airlines and Delta Airlines, among others, outsource their MRO program to third party service companies. As reported in USA Today, Mar 30, 2005, Delta Airlines expects to save $240 million over five years by outsourcing maintenance of its 344 jetliners. AAR Corp. could generate up to $50 million annually from providing regular maintenance for 137 of United's Boeing 737 jets, as reported in Crain Chicago Business, Mar 7, 2005. Meanwhile, commercial airlines have reduced their mechanics and maintenance staff from 4400 in 2004 to 2600 in the beginning of 2005. Not only are commercial airlines outsourcing their maintenance program to third parties, government sectors are also outsourcing their maintenance program. "Lockheed Martin [LMT] has been awarded a $6.5 million contract by the Brazilian government to provide comprehensive logistics support services for its six navy A-4 aircrafts and ten J52-P408 engines. LMT will provide maintenance services such as engine overhaul, flight line and deport level maintenance for the A-4s, and on the job training for technicians from the Brazilian Navy." (Potomac, May 10, 2005.)

The MRO in the aircraft business is mainly driven by following four factors [300].

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1. Increasing in demand for flights in a global marketplace.

2. Growth of low-cost airlines that outsource their majority of maintenance.

3. Refocusing core business by big and legacy airlines and, thus, sending more maintenance work to third parties.

4. Overall aging of airline fleets.

Not only are manufacturers of aircraft engines offering long-term service agreements for aircrafts, car manufacturers are also providing service contracts to customers for maintaining their loyalty and increasing satisfaction. Autobytel.com Inc., signed an agreement with Toyota Motor Corp., to make Toyota's Extra Care extended-service contracts on the Japanese car maker's vehicles purchased through Autobytel.com (Wall Street Journal, Jul 7, 1999). Ford Motor Co., (on Jun 10, 1999) agreed to buy Automobile Protection Corp., the administrator of Easy Care Vehicle Service contracts sold mainly through dealerships, for 180 million dollar as part of a push to keep customers after they buy a car or a truck (NY Times, Jun 11, 1999). Saturn uses its after service program to deliver better service and gains more customer loyalty [116].

Besides these two industries, long-term service agreements are offered under various names, forms, and types of products. For example, General Electric (GE) Company now sells service contracts for products, such as, jet engines, medical-diagnostic machines, and power systems. United Technologies Corporation's Pratt & Whitney offers service guarantees under the brand name "Fleet Management Programs", while GE sells its jet engines with a 10-15 year service agreement under GE's "Maintenance Cost Per Hour".

According to the above news items, long-term service agreements are gaining more popularity with the goal of being beneficial to both customers and providers. The obvious benefits of LTSAs are:

- It reduces maintenance, repair, and spare part inventory costs for customers, since an LTSA gives all responsibility to maintain a product to a provider.

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- It hedges the customers' risks of owning and using a product if they are not specialists in maintaining the product.
- It attempts to maximize availability of a product for a customer's usage.
- It generates a new stream of revenues for a provider.
- It establishes a long-term relationship between a customer and a provider, thus, enhancing customer loyalty for the provider.
- It increases an entrants' barrier to the provider's business.
- Finally, it benefits the whole economy by increasing productivity and safety.

However, the above benefits are realized only if the service is delivered satisfactorily.

1.2 Motivation of the Research

While long-term service agreements (LTSAs) are being offered and are used to gain a new and steady stream of revenues for a provider, the provider faces several challenges and risks in order to effectively deliver the service and manage an instant of an LTSA as well as a portfolio of LTSAs. These challenges include designing appropriate products and services, creating proper infrastructure supporting the delivery of LTSAs, developing operations and business strategies that are both strategically and tactically efficient, and drafting a mutual service contract.

1.2.1 Challenges in Managing a Portfolio of LTSAs

1.2.1.1 Product and Service Designs

Long-term service agreements change the concept of design for reliability, serviceability, and safety of products because LTSAs add the responsibility on a provider for maintaining the product's functionality. Moreover, the provider and the customer usually co-produce maintenance service of a product together. The design process needs to include interactions and communications between a manufacturer (provider) and a customer in order to effectively address and successfully respond to the customer's requirements and improvements.

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There are two levels of customer's involvement in the design process, i.e., a standardized design and a unique design. A standardized design is when the provider alone determines the product features with some possible but limited customer's specific modifications. Therefore, the provider can accurately estimate the future performance of the product. As a result, a standardized design is less risky than a unique design. A unique design is when the customer is completely integrated in the realization of the product and service design process. In this case, the provider cannot accurately estimate the performance of the product and may want to share the risks involved in the service delivery with the customer.

The product only facilitates the service delivery. The provider completes its service after the product functions and generates outputs as specified in the contract. The provider has to design its service delivery process that effectively and inexpensively delivers the required functionality of the product in order to create successful and profitable long-term service agreements. The service delivery needs to be consistent with the firm's strategy, meet customer's needs in a responsible manner, and establish a strong relationship with the customer.

In general, the service delivery provided includes maintenance schedules, repair specifications, operating conditions, and guidelines for operations and for failures and breakdowns. The provider also needs to plan for logistics, labor, infrastructure, and inventory in order to deliver the service efficiently. These plans depend largely on the reliability of the product. Fault Tree Analysis (FTA) and Failure Modes and Effects Analysis (FMEA) are among the techniques used at the design stage to achieve improved reliability and serviceability of the product. Besides variety of factors that product and service design needs to care for, the design of product, service, and their pertinent service components must be a proper combination of quality and cost.

1.2.1.2 Service Infrastructure

Service infrastructure supports the delivery of LTSAs. The service infrastructure includes a monitoring system, a maintenance system, and a supply chain management system. These three systems help the provider maximize the functionality

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and the availability of the product, and respond to problems, e.g., product's failure, faster.

Once a product is installed at a customer site, the provider needs to monitor its performance by performing diagnostic and prognostic tests. The performance of the product depends primarily on the condition or the health of the product. To observe the condition or the health of the product, sensors and Information Technology infrastructure are put in place. A monitoring system, for example, Health and Usage Monitoring Systems (HUMS) in aircrafts, is usually embedded in the product so as to alert the provider if the product shows suspicious behavior indicating proneness to failure [211]. The monitoring system helps the provider better assess and/or identify the cause of suspicious behaviors more accurately.

A condition based maintenance (CBM) approach is widely implemented in practice in order to correctly estimate the condition of a product. A condition based maintenance system usually includes a sensor module, a signal processor module, a condition monitoring module, a health assessment module, a prognostic module, a decision support module, and a presentation module [62]. In order to successfully implement CBM, issues corresponding to these modules, such as in Table 1.1[1], must be addressed.

Table 1.1: Challenges in CBM

Module	Description	Challenges
Sensor	Measure parameters such as temperature, pressure, vibration, etc., to determine the condition of a system	• Lack of robust sensors • High false alarm
Signal Process	Manipulate and extract data for the desired information	• Detection and characterization of rare events • Eliminating noise
Condition monitoring	Compare features against expected value or operational limits and output enumerated conditions.	• Real-time processing limitations
Health assessment	Determine current health of system or components	• Lack of fusion models for CBM • Lack of synchronous data
Prognoses	Predict future health of system taking into account estimates of past operations profiles	• Lack of predictive models
Decision Support	Automated decision making using patterns in the signal(s) or feather(s)	• Need to combine implicit and explicit reasoning • Hierarchical reasoning
Presentation	Display information and results to users	• Clear presentation that is easy to understand

[1]http://www.osacbm.org

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In addition to CBM, the infrastructure supporting the delivery of LTSAs includes a supply chain management system. The supply chain management system integrates material planning and management, spare part management, inspection management, and scheduling management. The supply chain management system is very important, since it contains all logistics to support the service delivery. Poorly managing the chain results in inefficient use of resources and higher costs of the service delivery.

1.2.1.3 Service Contract Drafts

Drafting a service contract is undoubtedly a challenge faced by the provider. It needs a lot of involvements from legal experts and engineers. Engineers must anticipate and specify conditions for operations, operations and maintenance guidelines, standards of procedures, and other engineering issues related to the safety of the product and its service provided. Cooperatively, lawyers have to draft a contract based on the information provided by the engineers. In several cases, a contract must also follow government regulations to ensure public safety and environmental protection. A contract must clearly state responsibilities and liabilities of both parties, since failures of these products can cause fatal results and, possibly, followed by several law suits.

These challenges need a careful attention by the provider in order to completely understand the nature and the risks of the service delivery. Risks of the service delivery pertain to adverse events that might affect the provider's service delivery. Without total comprehension of challenges and risks, the provider cannot effectively manage the service delivery of these agreements.

1.2.2 Risks of Managing a Portfolio of LTSAs

Risks are very important issues for the provider. The provider is exposed to risks based on its decisions and operations. They relate to adverse events or bad outcomes that happen during the service delivery. To efficiently reduce risks, the provider needs to understand the process of the service delivery and the nature of risks incurring during the delivery of LTSAs. After a thorough study of risks is performed, the provider can take advantage of different kinds of risks in order

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to manage LTSAs efficiently and profitably. We can divide risks into three main categories.

1. **Strategic risk** relates to designs of products and services. The provider analyzes uncertainties and develops plans for them. Based on these plans, the provider creates a standard of procedures for operations and maintenance of the product. Therefore, the strategic risk analysis gives a top-down view of the function of the business.

2. **Operational risk** is an uncertainty during operations. It depends on day-to-day operations, customers and services. Tactical or operational risk management is decisions made by the provider to handle situations as they arise. As a result, the operational risk analysis gives a bottom-up view of the function of the business.

3. **Extreme-event risk** is a risk related to rare events that cause a catastrophic impact on the product and/or its service delivery. An uncertainty due to new regulations imposed by the government which ensures greater public safety is treated as an extreme-even risk.

More detailed investigation of the risks of the service delivery will be discussed in Chapter 3. Risks are a major issue and we need to totally comprehend them in order to develop effectual service operations strategy and maintain the profitability of the service. Service operations strategy created must be a well balance trade-off between risks and costs. The dissertation develops an optimal risk management strategy for the delivery of LTSAs that produces the most effective and reliable but least costly service for the product to its customers. Next section will discuss the motivation and the main contribution of the research.

1.2.3 Motivation and Contribution

Risks are an important issue for managing LTSAs. Without thoroughly understanding risks, the provider cannot take advantage of interrelations between different kinds of risks of LTSAs and cannot develop a suitable risk management strategy

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which helps the provider avoid an exposition of extensive losses and endangerment of end-consumers' lives. The dissertation, therefore, focuses on creating a quantitative risk assessment and management framework of the service delivery of LTSAs.

Efficient management of LTSAs allocates the responsibility of risks to the most suitable hands as seen in Figure 1.2. A customer transfers risks of operations and maintenance of a product to a provider via a purchase of an LTSA. The provider plays the most central role in creating the service delivery, where it tries to manage risks by developing effective and efficient strategic risk management and service operations of the service delivery. Thus, some risks are borne by the provider after properly imposing operational constraints to the customer. Some risks which cannot be absorbed by the provider, e.g., extreme-event risks, are transferred to third parties, e.g., insurance companies via purchases of insurance policies. Risks of future technological changes and changes in government regulations are transferred back to the customer through renegotiation clauses in the contract.

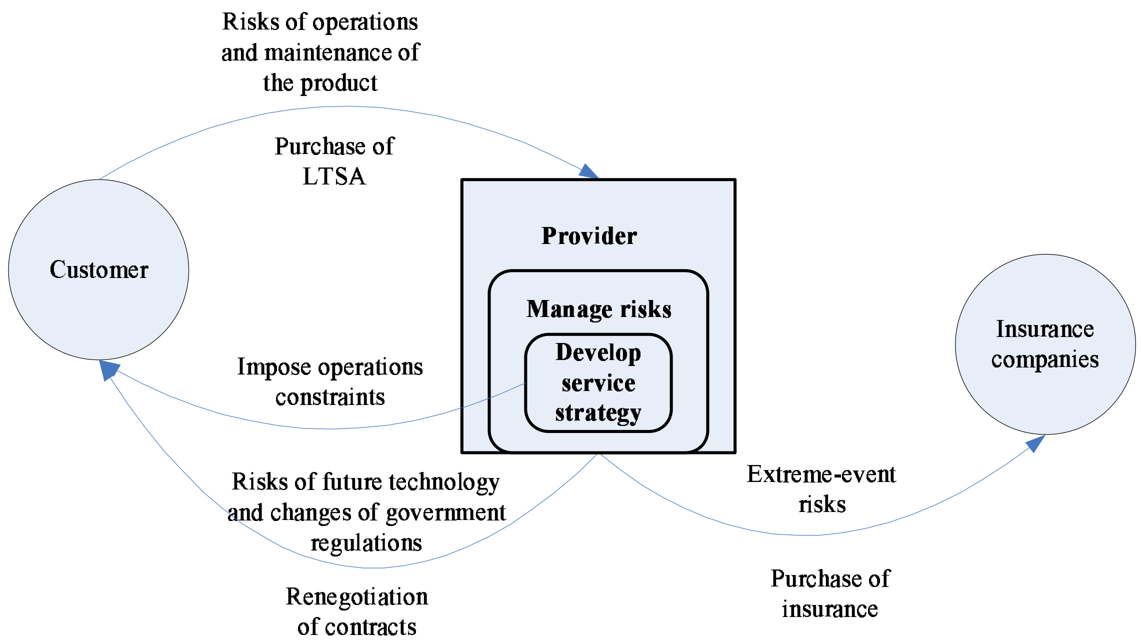

Figure 1.2: Effective management of LTSAs

The main contribution of the dissertation lies in the development of a thorough quantitative risk assessment and management framework used to manage a single as well as a portfolio of LTSAs. The framework mainly concentrates on strategic

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risks and on the service part of the service delivery. The rigorous framework for the service delivery of LTSAs provides a new understanding of the criticality and the importance of the interactions between the fields of product design, service design, manufacturing, and service management. The provider can apply the framework to create an appropriate risk management strategy and uses the developed strategy to sustain long-term profitability. The framework facilitates an in-depth analysis of service design for the delivery of LTSAs and can be instantiated for a specific type and model of a product after appropriately adapting the models to the context.

The dissertation provides new insights for the provider. These insights should enhance, facilitate, and improve the decision making process for the provider. The outline of the development of problem statement is discussed in the following section.

1.3 Problem Statement

Extending LTSAs to customers is a provider organization's strategy. There are many challenges for the provider in order to manage several agreements sold to one or more customers efficiently. The central theme of the dissertation is to develop a rigorous approach to create strategic plans that minimize risks in the provision of LTSAs from the provider's perspective. The strategic plans addressed in this research can be divided into two parts, i.e., strategic operations management and strategic business management of the service delivery. Strategic business management relates to long-term business decisions of managing LTSAs, while strategic operations management pertains to long-term decisions for service operations of the service delivery. This section begins by first addressing the strategic business management problem.

The problem of developing service delivery of LTSAs deals with designing end-to-end service operations for sustaining the functionality of a product for customers. In order to develop such a successful service strategy, the provider needs to understand risk of the service. In another word, the provider needs to source out what can go wrong, how it can go wrong, and what can cause it to go wrong. Without understanding risks, the provider cannot create an effective service delivery strategy for its customers. Risks that are relevant to the service delivery are, therefore, needed to be

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dissected, anatomized, and thoroughly studied so the provider can understand and take advantage of them effectively. We are able to find nine main sources of risks, i.e., design, manufacturing and installation, service, infrastructure, knowledge-based infrastructure, sale and marketing, finance, government regulations, and legal. In these nine categories, we can further group them into four classes, i.e., product risks, service risks, financial risks, and extreme-event risks.

Product risks concern how a product delivers its required functionality. This is the first step of quantitatively creating an effective service delivery strategy, since a product is a foundation of the service delivery. Meticulous design, manufacturing, and installation can significantly reduce product risks. Besides these improvements, the provider can also further reduce its risks via product maintenance. Without careful and proper maintenance, the product can no longer be hoped to function and deliver its required task efficiently and stably.

We then develop a problem for a multi-component product on which an LTSA is extended in product risks settings. The product consists of many components (parts), which degrade randomly over time. Once the product is installed at a customer site, the provider needs to constantly monitor its performance and perform prognostic and diagnostic inspections, since the customer's tolerance for failures is extremely low. With today's sensors technology, a monitoring system which is usually embedded within the the product provides the information, such as, temperature, vibration, and pressure. This information allows the provider to assess the condition or the health of the product, identify damage of the product and/or its parts, and develop a maintenance strategy based on the assessed condition of the product and/or its parts. In practice, the provider sets threshold levels for the product and its parts as an alert signal for a "prone to failure" stage. Once the conditions or the deterioration levels of the product and/or its parts exceed a threshold level, a trigger is set off for the provider to take a necessary maintenance action for the product and/or its parts in order to prevent failures, since a failure can result in very costly breakdowns and losses. Corresponding to each triggers, the provider wants to determine a strategically optimal maintenance action such that the long run maintenance costs are minimal. Analyzing the service delivery from product

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risks provides a good foundation for the problem, however, the provider's task is not yet finished. The provider needs to address other risks, e.g., service risks and financial risks, before the most effective service delivery strategy can be developed.

Physical products only facilitate the service delivery in LTSA practice. The provider completes its service when the product functions and creates output as pre-specified in the contract. While product risks are product specific, service risks affect every product in the provider's portfolio.

The strategically optimal maintenance action for the product does not take service risks into account. However, service risks are eminent in the service delivery. Without completely understanding risk exposures and their impact on the service delivery, the provider can be exposed to extensive losses and endangers the product's end-consumers. The second problem of the dissertation extends the framework from the product risks settings to include the risks of the service delivery. The objective of this problem is to develop a quantitative risk assessment and management framework at a single contract level to find a service operations strategy for an optimal service delivery of LTSAs. The provider needs to design its service operations strategy for the delivery of LTSAs that minimizes both risks and costs while fulfilling customer's service requirements. The framework begins by identifying sources of risks of the delivery of an LTSA. After that, models capturing the characteristics of the identified sources of risks and risk measures are developed in order to evaluate risks and find a proper service delivery strategy which achieves minimal risks and costs while guaranteeing the customer's needs. Service risks and product risks are extremely crucial for the provider. Developing a careful risk management strategy for these risks ensures the most effective service delivery for the provider as well as for its customers. However without a prudential financial management strategy, the provider cannot fully take advantage of a careful service risks and product risks management strategy.

The most prominent risk that the provider faces is financial risks. Financial risks concern risks of cash flow where the provider does not have enough fund or cash to pay for its service in any period of the contract. Without enough cash to pay for the service, the provider can no longer hope for delivering the highest and most

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reliably service to its customers. The provider, thus, needs to prudently construct its financial management strategy, which will minimize its shortfall risks.

The provider collects revenues and pays for the costs of the service delivery. The residual between the costs of the service delivery and the revenue is called cash flow. Financial risks relate to the risks of cash flow where there is a mismatch between revenues and costs. As a result, the provider faces financial shortfalls while delivering the service. At the instant level, the shortfall risks can be protuberant. The provider needs to carefully and properly manage its revenues and its costs of the service delivery. No matter how well the provider can manage its revenues and costs, the provider can still be exposed to substantial shortfall risks. The provider can seek to further reduce its shortfall risks by developing a proper hedging strategy to invest in financial instruments. The investment allows the provider to transfer positive cash flow to negative cash flow or to the area of shortfalls. The provider creates the transfer process by purchasing or investing its positive cash flow in selected assets, e.g., bonds, stocks, and options. The hedging strategy must be constructed such that the payoffs happen at the duration of the shortfalls in order to minimize the shortfalls. The challenges of this problem is to construct an optimal hedging strategy which minimizes both the shortfall risks and the costs of the hedging.

The strategic business decisions enforces decisions on strategic operations. The objective of strategic operations for a portfolio of products is to synchronize maintenance actions for products before they break down in order to efficiently balance costs of failures and costs of maintenance. After the products are installed at customers' sites, the provider is responsible for taking care of the products on which a contract is extended. The provider needs to develop a maintenance schedule for the products based on the reliability properties of their parts and the availability of resources, such as, repair crews and repair capacity. Hence, the provider would want to schedule the times to change or maintain the parts of the products before the products suffer from breakdowns, and when repair crews and repair capacity are available.

To serve the main objective of this research, we need to develop methodologies to solve these problems. Because LTSAs are offered for long periods (5-20 years) and

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involve many decisions, these strategic management problems are complex and challenging. Techniques based on continuous simulation, simulation-based optimization, and integer programming are developed to obtain optimal strategic plans.

1.4 Outline of the Dissertation

The dissertation can be divided into two parts. The first part develop strategic business decisions for the provider, while the second part focuses on developing an operational strategy. Chapter 2 provides a review of literature relevant to our research. The first part of the dissertation covers Chapters 3-6, and the second part of the dissertation is addressed in Chapter 7. In Chapter 3, we discuss and identify sources of risks of the service delivery, followed by the analysis of a multi-component product in product risks setting in Chapter 4. Chapter 5 develops a risk assessment and management framework to evaluate risks at a single LTSA level where we include product risks as well as service risks. While Chapter 5 studies risks collectively, Chapter 6 focuses particularly on financial risks where we develop an investment framework which minimizes shortfall risks for the provider. We digress from strategic business management problems to the a strategic operations problem in Chapter 7, where a study of the management of a portfolio of LTSAs is addressed. Finally, Chapter 8 provides general conclusions, addresses limitations, and suggests some directions for future research.

We start with the literature review of relevant research in Chapter 2. The chapter begins with a review of research concerning providers' challenges in order to deliver LTSAs efficiently, followed by a review of optimization models in maintenance management for LTSAs.

The risk analysis begins in Chapter 3, where sources of risks of the service delivery are identified. The sources of risks can be divided into 9 categories. The identification of risks allows us to develop a risk assessment and management framework which is general but can be instantiated for a specific type and model of a product after certain extensions and enhancements.

In Chapter 4, a strategic maintenance management problem of a single monitoring-enabled multi-component product is studied. The goal is to find a strategically op-

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timal maintenance strategy for a multi-component product in the product risks setting. In this problem, there are many components which suffer continuous stochastic deterioration with jumps in the product. The deterioration of the product is a function of the deterioration of its components and is analyzed using a continuous-time simulation. A search algorithm to find the optimal strategic maintenance actions is developed.

The analysis of Chapter 4 provides a footing of the analysis of service risks addressed in Chapter 5, where a rigorous risk assessment and management framework for an optimal service delivery of LTSAs is developed. The framework focuses on the service part of the delivery of LTSAs where several important sources of risks are included. The objective of the problem is to fulfill the service requirements imposed by the contract while minimizing costs and risk exposures during the service delivery. The framework allows simulation-based optimization to solve for the optimal service strategy and risk management, which can be used to develop a detailed tactical service delivery plan.

Chapter 6 analyzes financial risks for the provider after the provider utilizes the optimal service delivery strategy found in Chapter 5. The goal of the chapter is to further reduce financial risks for the provider, where we develop a hedging strategy that is least costly and minimizes shortfall risks. The hedging strategy appropriately transfers positive cash flow to the area of negative cash flow when they are needed.

Chapter 7 digresses to develop a strategic operations problem where it addresses the management of a portfolio of long-term service agreements from the provider's perspective. This chapter streamlines maintenance decisions made from the previous chapters. Our objective is to meet all the service requirements imposed by the contracts while minimizing total cost incurred. We develop deterministic integer programming models to generate the optimal maintenance schedules that minimize the total portfolio cost. This is followed by conclusions and possible future directions for the research in the area of LTSA in Chapter 8.

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CHAPTER 2
Literature Review

There are several challenges the provider has to face in order to develop an effective service delivery strategy of LTSAs and manage a portfolio of LTSAs efficiently. The study of the management problem of LTSAs is important, since it helps the provider deliver the most reliable but least costly service. The study involves many significant issues, such as, product design, product manufacturing and installation, long-range planning of the service delivery, maintenance strategy, service infrastructure and resource management, capital allocation, pricing strategy, and risk management strategy. The study of the management problem alters the concept of the service delivery, where it requires an integration of these problems to be addressed together. While these problems have been extensively studied in the past, they are often addressed separately.

This chapter provides an overview of literature pertinent to the dissertation. The literature review is divided into two parts. The first part (i.e., Section 2.1) addresses a broader view of challenges and strategic business management faced by the provider. In particular, the first portion focuses on product and service design, and risk management in the delivery of LTSAs. Section 2.2 concentrates on optimization of maintenance practices and inventory controls, since LTSAs transfer the responsibility for maintaining products to the provider. The provider needs to develop an optimal maintenance strategy that minimizes costs while fulfilling customer's service requirements.

This dissertation applies several solution techniques to solve the problems of efficient management of the service delivery of LTSAs. The solution techniques include continuous simulation and integer program. The strategic business management problems are solved using simulation techniques. For background on simulation techniques, the reader is directed to Law and Kelton [216], Kloeden et al. [205], and Glasserman [155]. The integer program, especially network flows, is used to solve the strategic operations problem. The reader should consult Ahuja et al.

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[15] and Nemhauser and Wolsey [277] for respective backgrounds.

2.1 Related Works for Challenges Faced by a Provider

There are several challenges faced by the provider to manage LTSAs effectively and efficiently. The challenges begin with product design, where the provider is now responsible to maintain products. Hence, the provider needs to design its products so that they are more reliable and easy to maintain. Besides the product design, the design and the management of the service delivery are very important because poor service design and service management may expose the provider to extensive loss, endanger end-consumers, and lead to the provider's bankruptcy. Fully understanding the process and the concept of product design, service design and service management helps the provider better assess risks of the service delivery and, thus, properly develop a potent risk management strategy. This section begins with an overview of challenges and techniques in product designs.

2.1.1 Related Works in Product Design

LTSAs change the concept of product design where they add responsibility for maintaining products to the provider. As a result, the provider should design its products so that they are most reliable and easy to maintain. Moreover since the maintenance of the products needs involvement with customers, product design process should integrate interactions and feedbacks from customers. These design concepts are essential, since decisions made during the early stages of the design process account for more than 80% of the life-cycle costs of the product [186].

Failure Modes and Effects Analysis (FMEA) is often used at a design stage to achieve the maximum product's reliability. It is a powerful tool assisting design engineers to improve the design of an equipment or a process. The process of FMEA starts with analyzing failures of components and proceeding to find their effect to the system. A key outcome of FMEA is a rank order of criticality of components. The criticality is ranked by using a risk priority number (RPN) which is a function of severity, occurrence and detectability of a failure [77, 148, 301, 352].

The most serious drawback of FMEA method is its incapability to address

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a trade-off between cost of failure and performance of a system. Enhancements to address this trade-off have been developed to new techniques, such as using behavior models, Advanced FMEA, and Qualitative Simulation models [138, 139, 206, 312, 346].

While FMEA is a bottom-up approach, Fault Tree Analysis (FTA) gives a top-down approach. FTA analyzes failures at the system level before tracing them down to the component level to find all possible causes and their origin [211]. FTA uses a tree to present failures and their causes. The tree shows the derivation of a single failure on the top of the tree to its root causes at the bottom of the trees [352].

Function Flow Diagram (FFD) and Reliability Block Diagram (RBD) portray the functional or the physical relationships and interfaces within a system. While FFD uses a block to represent a function, RBD uses a block to represent a component. Each block connects with an arc, which represents a relationship between components or functions [289].

Combining all these techniques creates relationships between causes and their consequences. This analysis leads to a comprehensive understanding of reliability properties of the product and provides mechanism to develop the highest reliability and easy to maintain product.

Even though the reliability and the life of a product are considerably increased through a rigorous design process, it is not enough for LTSA customers, since the customers have extremely low tolerance for failures. Hence, the provider has to design its service strategy to promptly respond to customer's problems and to prevent failures. Next section provides a background for service design and service management.

2.1.2 Related Works in LTSA Service Delivery Management

LTSAs offer an after sales service in order to increase the functionality of a product. Generally, The after sales services and LTSAs include 1.) Product installation, 2.) Personnel training, 3.) Routine maintenance, 4.) Emergency management, 5.) Service infrastructure management, and 6.) Software services [381].

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This dissertation mainly focuses on routine maintenance and service infrastructure management of the delivery of LTSAs. In another word, we concentrate our study in the service part of the service delivery. This section reviews relevant literature addressed in these areas. Specifically, the section concentrates on after sales service management, warranty management, maintenance management, and risk management.

2.1.2.1 An Overview of After Sales Service Management

Since 1990, the world economy has evolved from industrial society to service society where the service sector employs more than 70% of the total employment in the industrialized countries, such as, in USA, Canada, and Japan [147]. During this time, several manufacturers had achieved little profit growth, and only one eighth of 1000 largest manufacturers outperformed the S&P 500 [383]. Manufacturers, thus, need to refocus their strategy. The new strategy these manufacturers are using is to employ an after sales service to their customers, since the customers are now more sophisticated in choosing a product. Prices, special features, financial plans, and perception of quality and reliability of a product are no longer major decision criteria for customers especially for products that are highly competed among manufacturers in the market. Customers take after sales service factors, e.g., product warranty, parts availability, cost and quickness of the service, into their decision matrix [223, 262]. This after sales service accounts for 10-20 % of revenues. Moreover, it can generate revenues of at least 3 times greater than the original purchase cost of a product over its life cycle [207].

To manage an after sales service effectively, several researchers develop several frameworks for the after sales service business. Armistead [28] categorized the service based on customers' involvements and competitive criteria. The competitive criteria can be, for example, mean time to failure, mean time to repair, response time, near-zero-downtime, and safety [26, 27, 28]. Armistead and Clark [28] developed a strategy for human resources management used in the after sales service, where they adopted military terms to classify repair crews into five categories.

- *SAS* are specialists who solve unexpected problems and give a wide coverage.

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- *Regular Troops* are trained personnel who handle routine activities of maintenance.
- *Territorial* are customers who are trained by manufacturers to do routine maintenance.
- *Mercenaries* are agents or dealers who have been trained by manufacturers.
- *Enemies* are third party operators who compete for the same business.

Using this terminology, manufacturers can only benefit from enemies if the manufacturers have no control over products and the volume of the after service sales is small.

Lele [222] developed a 2-by-2 matrix using fixed costs and variable costs criteria. Lele classified service into four groups as follows.

- *Repairable*: Products which have high fixed costs but low variable costs
- *Disposable*: Products which have low fixed costs and low variable costs.
- *Never Fall*: Products which have high fixed costs and high variable costs.
- *Rapid Response*: Products which have high fixed costs and low variable costs.

Cohen et al. [116] used the provision of spare part as criteria for developing an after sales service framework. They proposed a 2-by-2 matrix based on service criticality (low or high) and service strategy (centralized or distributed), and concluded that low criticality was matched with a centralized strategy, while high criticality was matched with a distributed strategy. The other two options, which were high/centralize and low/distributed, were mismatched and must be avoided.

Buzacott [88] proposed a 5-by-5 matrix as shown in Figure 2.1 for categorizing services. His matrix had two dimensions, i.e., complexity of the service operations and the structure of a system. Johansson and Olhager [188] adapted a framework proposed in [176] for classifying service structure. Their matrix had two main dimensions, which were the nature of service (service offering), and the service process. Service providers can use the framework proposed in [188] to evaluate the effectiveness of their service process. If the service process supports or complements

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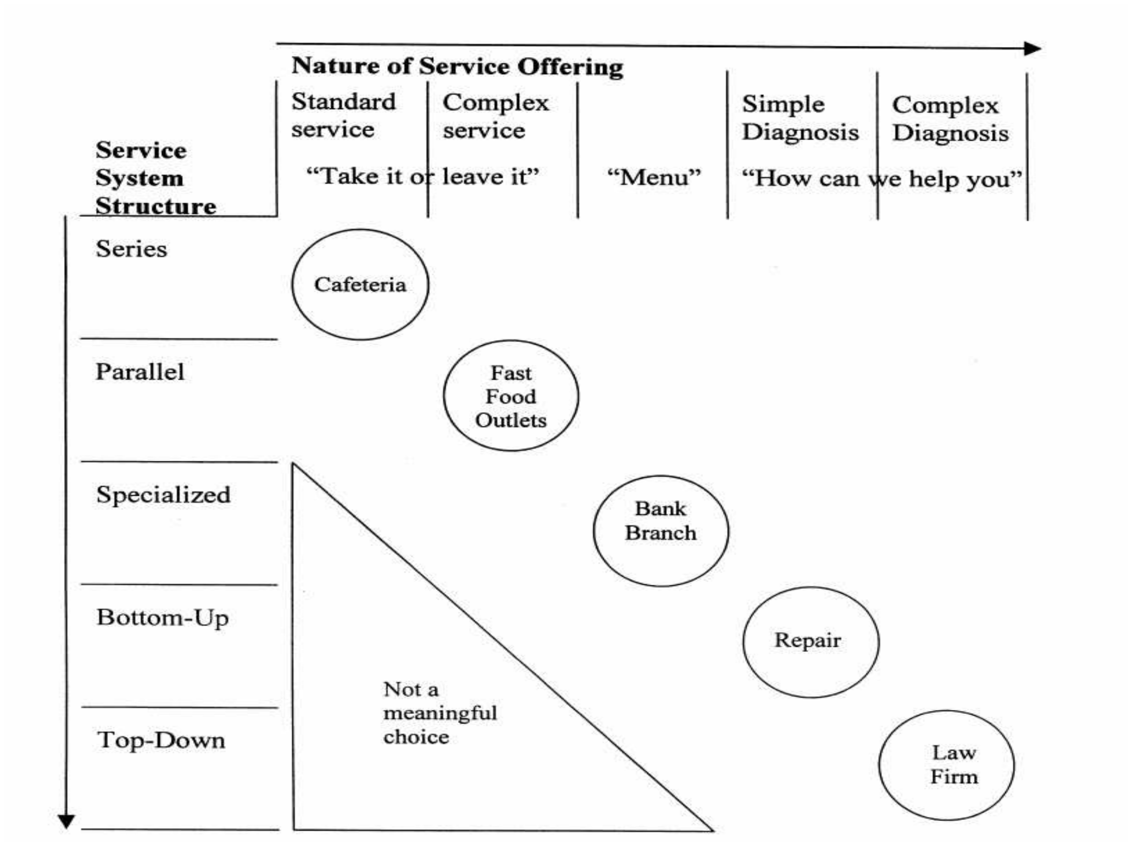

Figure 2.1: Classification of service structure (Buzacott, 2000)

the service offering, the profile will depict a straight vertical line in the framework shown in Figure 2.2. If the service process does not support the service offering, the framework will create a zigzag line. These frameworks help the provider qualitatively create a strategy for its after sales service program in order to respond to products' failures quicker. Moreover, the frameworks can be used as guidelines for the evaluation of the effectiveness of its program and provide top quality of the service without sacrificing costs.

Product warranty is an after sales service program which is widely used to give customers assurance on the quality of a product. In this regard, product warranty services are similar to LTSAs. The review of literature related to product warranty is provided in the following section.

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Aspects	Range			
Service offering	Unique	Selective	Restrictive	Generic
Markets and services				
Degree of customer/server contact	High			Low/none
Customisation	High			Low
Diagnosis offered	Complex			None
Range of services	Wide			Narrow
Demand variability	High			Low
Demand volume	Low			High
What do we sell	Capability			Commodity
Criticality for customers	High			Low
Profit generator	Profit margin			Volume
Rate of new product introduction	High			Low
How are orders won?				
Order winners	Availability of know-how, flexibility			Speed Price, quality
Order qualifiers	Price, quality conformance			conformance
Service process	Professional service	Service shop	Mass service	Service factory
Production				
Degree of customisation	High			Low
Degree of discretion	High			Low
Capability of handling variability	High			Low
Organisation	Flexible			Rigid
Technology focus	Effectiveness			Efficiency
Worker requirements				
Technical skills	High-level			Basic
Diagnostic skills	High-level			Basic
Interpersonal skills	High			Low
Facilities				
Location	Distributed			Centralised
Layout	For customer needs			For production efficiency
Key production task	Responsiveness			Dependability

Figure 2.2: The industrial service profiling framework (Johansson and Olhager, 2004)

2.1.3 An Overview of Product Warranty Services

Product warranty requires a manufacturer or a seller to compensate a customer when the product does not perform pre-specified functions during the warranty period [39]. Product warranty offers a protection for both customers and manufacturers. While it protects the customers from poor-quality or dysfunctional products, it protects the manufacturers from misuses of the product [110, 262].

Product warranty can be mainly divided into two main policies, i.e., free-replacement or pro-rate. Under a free-replacement warranty policy, a manufacturer is obliged to repair or replace a purchased product free of charge during the warranty period, while a manufacturer reimburses its customer partially under a pro-rata

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warranty policy. The reimbursement depends on age of the product at the time of failure [71, 111].

There are two major decision variables for a manufacturer to determine the price of the warranty service. These decisions are warranty price and warranty period. Warranty price depends on replacement costs, labor costs, diagnostic costs, and maintenance costs. Several researchers find the optimal warranty price from warranty service cost per product failure, warranty cost per unit time over the warranty period of a product, or warranty cost over the life cycle of a product [39, 73, 110, 262]. The optimal warranty period depends principally on the reliability the lifetime distribution of a product under some pre-specified working conditions [74, 229].

One of the main competitive strategy among manufacturers is to extend longer warranty periods. For example, the warranty period for cars is now 60 months compared to 3 months during the thirties. Within the warranty periods, manufacturers offer a free-preventive maintenance for customers in order to control the deterioration of the product and, thus, to reduce the possibility of failures. Integrating preventive maintenance with warranty for products can enhance the life of the products and is desirable especially for products with high failure costs [202].

Even though product warranty services share several similarity with LTSAs, there are significant differences between the two as pointed out in Gupta et al. [162]. In short, an LTSA offers a wider coverage for a product than product warranty. While product warranty reimburses customers only when a product is faulty, an LTSA compensates the customers when the product is faulty and when the product cannot function as specified in a contract, since an LTSA offers a guarantee on the functionality of a product. Therefore, manufacturers (providers) need to be more aggressive in offering the service package for an LTSA than product warranty.

Frameworks for after sales service management and product warranty management help the provider create an effective strategy for the delivery of LTSAs. Adopting these frameworks, the provider can benefit from them by creating service that responds to customer's problems quicker and offers better service quality without sacrificing costs of the delivery.

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2.1.3.1 An Overview of Maintenance Management

A provision of LTSAs deals mostly with maintaining products for customers. With extremely low failure's tolerance from customers' point of view, the provider has to act proactively in order to prevent failures. Hence, maintenance management is very important to the provider. This subsection starts with providing a review of maintenance management approach, followed by maintenance policy.

Maintenance Management Approach

Total Productive Maintenance (TPM) is a maintenance approach that maximizes the productivity of a product (equipment) by avoiding six major sources of losses, which are (1) equipment failures, (2) setup and adjustment time, (3) idling and/or minor stoppages, (4) reduced speed, (5) deflections in process, and (6) reduced yield [274, 357]. TPM is also used to reduce and to control the variation in process [31, 325]. Under TPM, a small team is assembled to study the relationship between maintenance and production and to create a maintenance strategy to improve the overall equipment efficiency (OEE), where OEE is a product of availability, performance efficiency, and quality rate. In general, TPM teams try to enhance the performance of a product by improving equipment design, production processes, and maintenance processes. The reader who is interested in TPM should consult [96, 274, 389].

Reliability Center Maintenance (RCM) is a technique used to develop a preventive maintenance schedule which is well balanced between costs and benefits [311]. The main objective is to reduce maintenance costs while enhancing safety and reliability of an equipment [92]. The analysis of RCM can be divided into four parts, i.e., (1) preparation, (2) system analysis, (3) decision making, and (4) implementation and feedback. RCM can be further divided into two approaches, namely a p-RCM and an f-RCM. A p-RCM or Probabilistic RCM uses probability to make a maintenance decision, while an f-RCM or Fuzzy RCM allows subjective assessment and experts' opinion to make a maintenance decision [309, 132].

Risk Based Maintenance (RBM) is a technique used to find a maintenance action from the relative loss, benefit, or risk function of possible maintenance actions

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[24]. RBM can be broken down into three modules, i.e., (1) risk determination, (2) risk evaluation, and (3) maintenance planning [200]. Risk determination module identifies risks and estimates their consequences. Risk evaluation module evaluates risks defined in the risk determination module and compares them with a setup acceptance criteria. Lastly, maintenance planning module evaluates maintenance options and their risks. The reader who is interested in RBM should consult [24, 126, 243, 375].

Business Centered Maintenance (BCM) is based on the business objective of a firm. The business objective is then transformed into a maintenance objective. The goal of BCM is to maximize the contribution of maintenance to a firm's profit rather than focusing on maximizing reliability of equipment [379].

Maintenance Policy

We can divide maintenance policy into two main categories, a corrective maintenance and a preventive maintenance. A corrective maintenance is carried when a product fails, while the provider is more proactive where a product is preemptively maintained under a preventive maintenance policy. Since LTSAs offer near-zero failures, the review concentrates on preventive maintenance policies

Preventive maintenance can be further divided into usage based maintenance policy (UBM), condition based maintenance policy (CBM), and opportunistic based maintenance policy (OBM) [191, 302].

Maintenance in UBM policy is carried out at predetermined period (e.g., age or time), or by events which is pre-specified by a standard of operations. The objective of UBM is to reduce breakdowns by maintaining a product after the product has been operating for a specified time or produces a pre-specified number of outputs, e.g., maintenance every 6 months, maintenance every 750 flight hours, maintenance every 5000 miles, etc.

Maintenance in CBM is activated based on the condition of a product. The condition of the product can be assessed through a routine inspection or can be observed continuously from a monitoring system. In general, a maintenance action is performed if the condition of the product exceeds a threshold value or a warning

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limit. CBM is now gaining more popularity, since there are several innovations for sensors technology and new estimation techniques which give more accurate assessment for the condition of the product. Hence, CBM helps the provider save maintenance costs and reduce failures simultaneously [17, 90, 191, 302, 379].

Maintenance in OBM is carried out when a product is idle due to some components' failures. The provider takes this opportunity to maintain other non-failed components in order to enhance the effect of maintenance and reduce maintenance downtime of the product. OBM can also be carried out during low utilization periods [302, 191].

Effective maintenance helps the provider reduce maintenance costs and failures as well as enhance the functionality and the life of a product. To achieve the most effective maintenance strategy, the provider needs to combine maintenance policies and develop appropriate parameters for the combined policy, e.g., how frequent for a routine maintenance in UBM, the triggered threshold for maintenance of a product in CBM.

Failures are not deterministic. Hence the costs of the service delivery are not deterministic, but the revenue received is deterministic. As a result, there are some risks of mismanagement of the cash flow by the provider. Besides the financial risks, there are several risks during the service delivery, e.g., risks of poor product maintenance, risks of poor management of service infrastructure, etc. Next section provides the background of risk assessment and management framework addressed in the literature. For the extensive discussion of the sources of risks of the service delivery, the reader is directed to Chapter 3.

2.1.4 An Overview of Risk Management in Long-Term Service Agreements

Efficient management of LTSAs allocates risks to the most suitable hand, where customers hedge the risks of owning, using and maintaining a product by purchasing an LTSA. The provider acts like a risk bearer by accepting transferred risks from its customers after appropriately imposing operational constraints to the customers. The provider, therefore, needs to completely understand the risk profile

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of the service delivery of LTSA in order to create a proper risk mitigation strategy and to develop an appropriate service delivery strategy.

This section provides an overview of risk assessment and management for products and service delivery, followed by a discussion of financial risks. Risk assessment and management for products and service delivery quantifies the likelihood of adverse events and creates plans for mitigate them, while the financial risks relate to risks of cash flow.

2.1.4.1 Risk Assessment and Management for Products and Service Delivery

Risks are often perceived as a bad outcome and are also a mixture of fact, value and fear [119]. In general, risks can be defined in two ways, subjective risks or objective risks. Objective risks are a numerical variation which occurs when actual losses differ from expected losses. Mostly objective risks are measured statistically, for example, standard deviation, variance, moment, etc. Subjective risks refer to the mental state of an individual to the result of a given event [160].

Typically, risks can be measured as a probability of occurrences and/or consequences. Several researchers equate risk as a product of the probability of occurrences and its severity (consequence) [22, 163].

$$Risk = \texttt{Occurrence of an event} \times \texttt{Severity of an event} \tag{2.1}$$

Complementing with using Equation 2.1 and being able to properly define risks, a practitioner should be able to answer the following questions [260].

1. What can go wrong?

2. How likely is it?

3. What are its consequences?

By asking these three questions, researchers developed a framework to quantify risks. Among several Quantitative Risk Assessment techniques, Probability Risk Assessment (PRA) is widely used in several industries, such as, nuclear energy,

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railway and air transportation, and pipelines [175, 260]. PRA is a technique defining and quantifying the probability of an adverse event. Risk measures, which are used in PRA, indicate the severity of an event or an accident, e.g., potential loss of lives (PLL) and fatal accident rate (FAR). FAR represents the average of fatalities per 100 million exposed hours. In general, a PRA has three main stages as summarized in Table 2.1 [163].

Table 2.1: Three primary steps toward risk management in safety

Stage	Question	Actions
1. Risk Identification	What can go wrong?	Identify sources of risks
2. Risk Quantification	How likely is it?	Assess possibilities of events
3. Risk Evaluation	How can we avoid it?	Create a mitigate plan

Several techniques have been used to identify sources of risks in PRA [175, 91]. The example of these techniques are as follows.

- *Preliminary Hazards Analysis (PHA)* is a semi-quantitative analysis which tries to identify all potential hazards of a system.
- *Failure Tree Analysis (FTA)* is a bottom-up approach where it begins from an undesirable event and works backward to find its causes.
- *Event Tree Analysis (ETA)* is a top-down approach where it starts with an adverse event and then searches to find its possible outcomes.
- *Failure Modes and Effects Analysis (FMEA)* is an inductive analysis to find all possible failure modes and identify their sources.
- *Hazards and Operability Studies (HAZOP)* is an extended FMEA where it includes a failure of operations in the analysis.
- *Cause-Consequence Analysis (CCA)* is similar to ETA, but the difference is that instead of starting from an adverse events, CCA starts from initiating challenges.

Once sources of risks are identified, the provider needs to assess the probability of occurrences of adverse events. The probability of adverse events is assessed by

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combining FTA and ETA together. Since ETA helps us better understand effects of an adverse event, while FTA helps us comprehend causes of an adverse event, combining ETA and FTA generates a complete understanding of adverse events. The probability is found by multiplying the branches of trees together [225].

Finally, PRA utilizes the probability of occurrences of adverse events to control and mitigate risks. Trade-off analysis should be performed in order to find the acceptable region of risks. Since risks are often subjective, the acceptable level of risks depends on the definition and the perception of risks of an individual. In general, there are four main premises used to define risks [242].

1. *Maximizing expected utility* is based on cost-benefit analysis. Its most drawback is to assign monetary value to intangible benefits or losses.

2. *Rawlian approach* is based on the overall benefit of a society.

3. *Paretian approach* is based on the analysis of finding the worst case scenario.

4. *Nietzschean elitism* is based on the analysis of finding the best case scenario

Regardless of the definition of risks, there is a level of risks where risks above this level are unacceptable, and another level of risks where risks below this level are negligible. The middle zone between these two levels is called As Low As Reasonably Achievable Principle (ALARP), where risks in this zone are acceptable if and only if the benefit of handling these risks is more than the benefit of avoiding it. Figure 2.3 depicts the concept of ALARP zone.

PRA contains a large amount of product-related information which helps engineers systematically monitor the performance of the product, alert the user if quantified risks exceed their acceptable level, and better manage the risks. Moreover PRA can generate different types of information, such as, long-term and short-term information. The long-term information is used to get an insight on the past history in order to create strategic plans for risk management, while the short-term information is used to instantaneous evaluate risks from tactical operations perspective [185].

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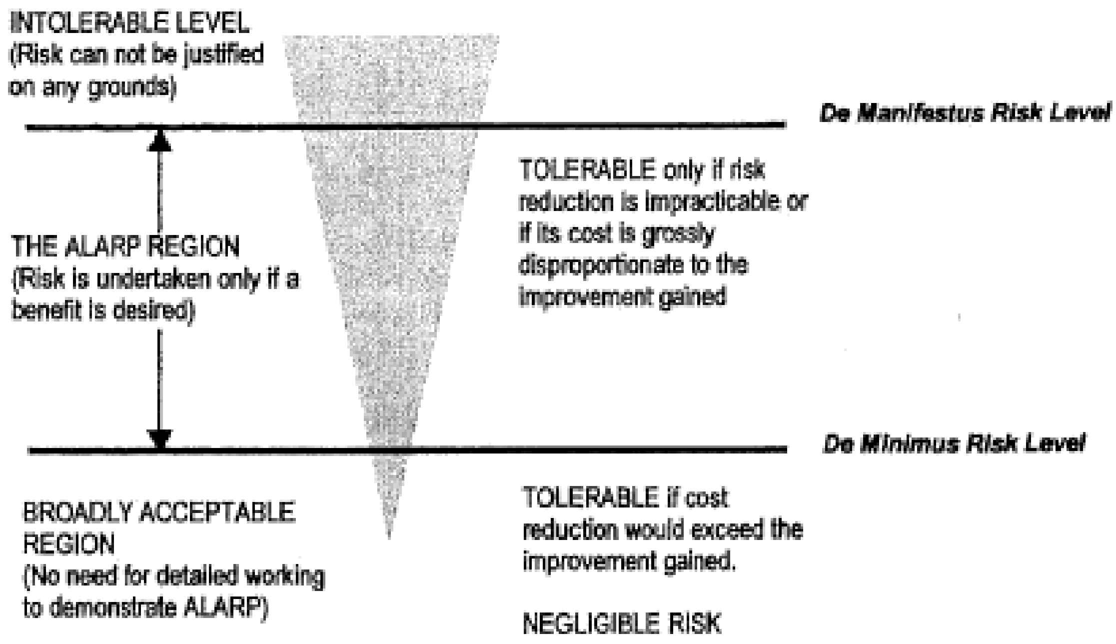

Figure 2.3: The figure presents the concept of ALARP zone (Marszal 2001)

The obvious drawback of PRA is that the analysis for a complex system requires a very large database and is time-consuming. Many events and/or components can be neglected in an analysis, yet providing a meaningful result of PRA. Cepin [95] enhanced a computation analysis of PRA by proposing a systematic approach to truncate the negligible contribution of some results of PRA. Another drawback of PRA is that it does not give an insightful value. PRA only provides a probability of an adverse event for practitioners. Hence, practitioners cannot completely sacrifice their judgment and only believe in the numerical value providing by PRA [141]. Some researchers, such as, Oien [285, 286] and Roqvist [315] enhanced PRA by including qualitative risk assessment to the traditional PRA.

2.1.4.2 Financial Risks

In the section, we provide a brief overview of risk measures and risk management techniques for financial risks. The financial risks concern risks of cash flow and play a critical role in making a profit for the organization. The financial risk management is essential for the provider because of different patterns between the cash

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flow of assets and of liabilities. Should the provider mismanages its cash flow, it can get into a very serious financial distress. The provider, therefore, has to manage relationship between the costs of the service delivery and its revenue received effectively.

Financial Risk Measures

Before the provider can assess its risks, it needs to know how to measure its risks first. Mathematically, risk measures are a mapping from a set of random variables on some measured space to the real line. Most importantly, the provider must be able to use these quantified risk measures to capture its preference of risks [125]. Risk measures can be defined into two classes, i.e., risk measures defined in term of axiomatic definitions and risk measures defined in term of theories of choice [125, 371]. The risk measures defined in term of axiomatic definitions are created from a set of desired properties that the risk measures should satisfy [29].

Markowitz [240] developed a portfolio theory where he proposed to use variance to measure the risk of a portfolio. The obvious drawback of using variance to be a measure of risk is that the variance takes into account both good and bad risks. In general we do not care for good risks. The only risks we need to manage is bad risks. Hence, several downside risk measures have been introduced. Among other measures, Value at Risk (VaR) is widely used as a risk measure in financial institutions. VaR is an α-quantile risk measure based on a probability of loss during specified periods in which the loss is expected to occur. Given a confidence level, $\alpha \in \{0, 1\}$, the VaR is the smallest number such that the loss of a portfolio L exceeding a number l is less than α, or mathematically:

$$VaR_\alpha = inf\{l \in R : P(L > l) \leq 1 - \alpha\}. \tag{2.2}$$

There are several approximation methods and estimation techniques used to compute a VaR, such as, historical simulation, analytic method or the delta-normal method, and Monte Carlo Simulation. Historical simulation depends on historical data, while the delta-normal method finds VaR analytically by assuming that the loss distribution of a portfolio is normally distributed. Monte Carlo technique randomly creates several scenarios, and VaR is calculated according to the worst losses

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from the generated scenarios. Among these three methods, Monte Carlo simulation is the most preferable one due to its ability to measure risk accurately [294]. Other techniques used to calculate and to enhance the accuracy of VaR can be found in [150, 215, 342]. Several research, such as, in [5, 294, 305], examine the trade-off between the accuracy and the computational time among several computational VaR approaches.

Even though VaR is very famous, it is far from being a complete risk measure. The first drawback of VaR is that VaR only retains information about the maximum loss given a certain confidence level α. It does not contain any information on a severity of losses for any other α. The second drawback is that VaR is only a good measure if a loss distribution is symmetric, since VaR, variance, and standard deviation ignore the tail of a loss distribution. Moreover VaR is not a *coherent* risk measure because it is not sub-additive, i.e., $VaR_\alpha(P_1+P_2) \nleq VaR_\alpha(P_1)+VaR_\alpha(P_2)$ where P_1 and P_2 denote the return of a portfolio [29, 249]. Because VaR is not sub-additive, diversification of a portfolio may not reduce the risk measured using VaR. Lastly, VaR is difficult to control and optimize, since it is non-smooth, non-convex, and is a multi-extreme function with respect to positions. As a result, it is possible that we can produce some disastrous errors when we use VaR as a risk measure [244].

Since VaR has several drawbacks, other measures, such as, Conditional VaR (CVaR) and Expected Shortfall (ES), have been introduced to remedy these drawbacks. In the case of continuous random variables, ES is equal to CVaR [358]. By definition, α-CVaR is the expected loss exceeding α-VaR. For example, given $\alpha = 0.95$, $CVaR_\alpha$ is the average of the 5% worst losses. Mathematically, CVaR is defined as follows.

$$CVaR_\alpha(x) = E(z|P(x,z) \geq \alpha), \tag{2.3}$$

where $P(x,z)$ = the CDF of loss associated with decision x.

It has been shown by several authors that CVaR is better than VaR when the loss distribution of a portfolio is not normally distributed or symmetric [29, 387]. Pflug [297] proved that CVaR is a coherent risk measure. However, CVaR is computationally expensive because the estimation of the errors of CVaR is much

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greater than that of VaR [387]. Rockafellar and Uryasev [313, 314] showed that α-VaR and α-CVaR for some settings can be calculated simultaneously using a convex optimization theory. Even though several research shows that CVaR is a coherent risk measure, Acerbi and Tasche [7] showed that CVaR is still an incomplete risk measure where they proved that CVaR, especially in a continuous case, is not a coherent risk measure because it fails the sub-additive property. However, the authors suggested CVaR was more effective than VaR. The reader who is interested in VaR, CVaR, ES, and other risk measures should consult [6, 41, 61, 102, 135, 232, 233, 241, 364].

Researchers and practitioners apply risk measures to measure risks and develop a management plan for organizations. In general, risk management measures risks to develop pricing strategies, hedging strategies, portfolio optimization, and capital allocation. Next, we will provide an overview of risk management in a financial framework.

Financial Risk Management

Risk management is a systematic approach to identify, evaluate, and manage risks. After sources of risks have been identified and risks are evaluated, the provider needs to decide what to do about them. In general, the provider wants to control the risks or to set aside some fund to pay for the expected loss. There are several strategies used in financial risk management, but they share the similar objective which is to minimize the loss should an adverse outcome occurs. In this subsection we provide a broad overview of financial risk management pertinent to our research by beginning with a brief overview of hedging strategies.

Hedging

Hedging strategies are a strategy which the provider uses to offload its risks. In another word, hedging can be perceived as an insurance of an asset against negative events. Derivatives are normally used for hedging. Derivatives or derivative securities are a financial instrument whose value depends on underlying assets [184]. In general, derivatives have two forms, future or forward contracts and options. A

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forward contract is an agreement to buy or sell something for a certain price at a certain future time. Similar to a forward contract, a future contract is an agreement to buy or sell something in future, however, a future contract is traded on an exchange. Options are a right that gives an opportunity to buy or sell an asset to the counter party at a predetermined price in the future. An option, which gives a right to buy an asset, is called a call option, while an option, which gives a right to sell an asset, is called a put option.

To construct a hedging strategy, measures, such as, delta, gamma, theta, and vega, are needed [184]. Delta, gamma, theta, and vega (or the Greeks) compute the sensitivity of an option to changes of the underlying parameters. For mathematical descriptions of the Greeks, the reader should consult [184]. The provider constructs hedging strategies by investing in financial instruments, e.g., bonds, stocks, and derivatives, whose payoffs occur at time of shortfall. The main objective of hedging strategies is to construct least costly hedge with minimal risks. In order to solve for optimal hedging strategies, several approaches, such as simulations, numerical analysis and partial differential equations, are proposed, [115, 295, 382].

Portfolio Optimization

In general, a problem of portfolio optimization deals with selecting a proportion of assets i in order to maximize profit or to minimize risks by diversifying invested assets. Assets can be stocks, options, future or forward contracts, etc. Markowitz [239, 240] developed a portfolio theory where he used a variance as a risk measure to find a portfolio obtaining highest expected return but minimal variance. The framework of Markowitz has further been extended to include more than two assets and multi-period case, such as, in [117, 221, 226, 250, 251].

Portfolio optimization problems can be extended into more complex and sophisticated problems. For example, some problems allow investors to impose some constraints on a terminal date or on every intermediate date, e.g., in [133, 153, 187]. In these problems, an investor is guaranteed a minimal value of a portfolio on a terminal date (European guarantee) or on every intermediate date (American guarantee). Norland and Wilford [281] assumed that given a set of expected return

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there should be one portfolio which reflects the optimal allocation for any global investors. In their setting, they argued that the mean-variance framework can introduce a bias to optimal portfolios. The bias caused the optimal portfolios to over-invest in domestic cash securities. As a result, the authors suggested investors to model a mean-variance framework from an excess return point of view instead of a total return.

Topaloglou et al. [370] developed a simulation-based optimization for multi-currency asset portfolio selection problem such that CVaR was minimized. Instead of a simulation-based optimization, a linear programming model is proposed in [209]. Agarwal and Naik [10] investigated risk exposure of a hedge fund using CVaR framework. The authors showed that the mean-variance framework would underestimate the left tail risk of a hedge fund. Krokhmal et al. [209] developed a linear programming model to find the optimal portfolio of a hedge fund where CVaR is minimized.

Ballestero [40] developed a portfolio optimization model using a mean-semivariance instead of the more traditional mean-variance framework, since investors often define risk as a chance of adverse results. Hence, a downside risk measure is more appropriate. Similar to Ballestero [40], Satchell et al. [320] developed an analytical model to minimize the downside risk of a portfolio. In their model, the weight function is an exponential function. While the authors in [40, 320] used the expected return to calculate downside risks, Fishburn [146] proposed a more generalized model where the downside risks are calculated using a threshold set by an investor. Further review on a portfolio optimization under different risk measures can be found in [123, 353].

Asset Liability Management

Asset liability management (ALM) problems aim to match assets with liabilities through investments of financial instruments. An obvious example of ALM problems is a bond portfolio immunization problem, where an investor invests in several bonds in order to match their maturities, durations, and/or convexities with the investor's liabilities [43, 70, 304].

ALM has more dimensions than a bond portfolio immunization, where an

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investor can invest in a variety of financial instruments such that the portfolio of instruments provides a perfect matching with liabilities. As a result, ALM problems share these similarities with portfolio optimization problems. However, the objective function is different where the portfolio optimization problems try to maximize an investor's wealth. ALM problems seek to minimize risks of cash flow mismatch.

There are several techniques that solve ALM problems successfully with reasonable computational effort, e.g., using stochastic programming or stochastic differential equations. Stochastic differential equations solve ALM problems analytically. As a result, the setting of ALM problems is relatively simple and unsophisticated [253]. To study more sophisticated strategies and settings, stochastic programs are introduced to study ALM problems. Since stochastic programs are computationally expensive, researchers need to develop an efficient method to solve the problems. Among various methods, scenario-based models and dynamic programs are widely adopted.

In scenario-based models, a scenario tree is created by either using appropriately chosen distributions or by a set of sample paths. After a tree is created, the problem is formulated as a stochastic program [208, 347]. Dynamic programming approaches try to solve a complex multi-period problem one stage at a time. This approach is suitable for relatively small set of state variables because it yields high quality solutions. However, the curse of dimensions is applied when the state variables increase [291].

Previously, our discussion focused on general challenges and business management of LTSAs. Next section reviews related works in the area of strategic operations management problems. In particular, we focus on maintenance management and service infrastructure management problems.

2.2 Optimization Models Related to Management of LTSAs

In this section, optimization models related to strategic operations management of LTSAs are discussed. The strategic operations management problems of LTSAs are similar to three different problems addressed in the literature, machine replacement problems, maintenance scheduling problems, and inventory pooling prob-

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lems.

The *machine replacement problem* deals with replacing an old machine with a new one. As a machine gets older, it will be more costly to operate both from the operational cost and the maintenance cost perspectives. Costs are reduced by replacing the old machine by a new one when the machine reaches a certain age. The *maintenance scheduling problem* addresses a trade-off between preventive maintenance and corrective maintenance in order to develop a maintenance schedule which minimizes the total cost. The *inventory pooling problem* determines the optimal inventory kept in each warehouse in order to have minimal backorders and transportation costs.

The strategic operations management problems of the delivery of a portfolio of LTSAs relate to these problems. Parts of a product, on which an LTSA is extended, should be replaced when they get older and are more likely to breakdown, which is similar to the machine replacement problem. However from the product perspective, since they are high cost and long-lived, they are used until the end of the planning period. The products undergo inspections and maintenances without being replaced which is similar to the maintenance scheduling problem. Meanwhile, the level of inventory kept in provider's repair facilities is similar to the inventory pooling system, where we need the minimal number of inventory kept in each repair facility such that the costs of transportation and a number of backorder are minimized.

2.2.1 Maintenance Scheduling Problems

Maintenance can be divided into two main categories, a preventive maintenance and a corrective maintenance. A preventive maintenance is a preplanned maintenance of a machine, while it is in a working condition. In contrast, a corrective maintenance is an unplanned maintenance restoring a machine from failure or malfunction to a working stage.

A maintenance scheduling problem addresses a trade-off between preventive maintenance and corrective maintenance, i.e., a trade-off between failure costs and costs of maintenance. The objective of the maintenance scheduling problem is to find a maintenance schedule (whether to repair, to replace or both) of a machine or

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a system such that the expected long run cost is minimized.

2.2.1.1 Perfect Repair or Replacement Models

This subsection focuses on a replacement model or a perfect repair model, where a system is restored by a replacement of a similar system in a scheduled period or at the time of failure. This subsection starts with an age replacement model or a block replacement model, where a system under the age replacement strategy is replaced at a certain age or at failure [154]. Bhat [69] argued that the block replacement policy had many wastes especially for multi-component systems, since period T in which a system was replaced, every component in the system was replaced, as a result some components which were almost new were also replaced. Hence, Bhat [69] and Berg and Epstein [67] modified this model to allow an almost new component to remain in the system.

Taylor [366] studied a system which had an increasing failure rate and was damaged only by shocks. In his model, damage of the system was accumulated. He proposed the optimal policy, where the system was replaced upon failures or if the total damage of the system exceeded a threshold level. Nakagawa [266] used renewal theory to study the additive damage model and proposed that if $M(K) > \frac{c_2}{c_1 - c_2}$ then there existed a unique optimal k^*, where k^* was a replacement threshold and $k^* = \frac{c_2}{c_1 - c_2}$, where c_1 was a corrective replacement cost and c_2 was a preventive replacement cost. His model was similar to the New Vendor model in the inventory theory. However if $M(K) \leq \frac{c_2}{c_1 - c_2}$ then we chose $k^* = K$, or the system was replaced at failures. $M(x)$ was a renewal function.

Abdel-Hameed and Shimi [4] assumed that a system was damaged only by shocks. The shock process followed a Poisson distribution with parameter λ. They proved that if the cost function was convex, there existed a unique optimal solution. Boland and Proschan [80] proposed a periodic replacement model, where a system was replaced periodically in period kT, k=0,1,2,..., or at shocks. They assumed that their shock process was non homogeneous Poisson and the operating cost was a linear function of the number of shocks. In their study, the optimal periodic replacement period, T^*, which minimized the expected long run cost, was found

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using a transformation technique transforming a non homogeneous Poisson process to a homogeneous Poisson process. The cost model in [80] was generalized in [76] to include some randomness in a cost function. Abdel-Hameed [2] showed that the result in [80] was hold to any counting process.

Several researchers study a replacement problem, where a system deteriorates over time. Klien [204] studied an inspection-maintenance-replacement problem and used a Markov chain to find an inspection/maintenance schedule which minimized an average cost per time between inspections. He assumed that the deterioration of the system was found only by inspections. At each inspection, a decision maker decided whether to keep or to replace the system. If the system was kept, the decision maker further decided whether it needed to be repaired now or could wait until the next inspection. Generally if the system was replaced, it returned to an initial state. If it was repaired, it returned to the stage between the current state and the initial state.

Aven and Bergman [34] assumed that a system was under a condition based maintenance, and the information of a system was always available and perfect. They set up a replacement problem using a counting process. Their method of finding the replacement period was similar to that of finding a stopping time of a counting process. Lam and Yeh [213] also assumed that a system was under a condition based maintenance, however, in their study the deterioration of the system was identified only by inspections. Instead of replacing a system when it suffered a certain amount of cumulative damage, Beichelt [58] proposed a new policy, where a system was replaced if the cumulative maintenance cost exceeded a threshold cost. He argued that the life distribution of a system was very hard to estimate, however, the maintenance cost data was always available. Thus, replacing a system using the cumulative maintenance cost scheme was more appropriate. The reader who is interested in a non homogeneous shock models should consult [1, 137, 323]. For further studies in stochastic and deterioration models, the reader is directed to [106, 136].

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2.2.1.2 Minimal Repair Models

A repair is defined differently by different researchers. Generally, it means to restore a system back to a better stage. The replacement or perfect repair models and the repair models have many similarities. However, the difference between the two models is that, for the replacement model the system is **replaced upon its failure or a predetermined age or time**, but for the repair model, the system is **repaired at its failure**, but it is replaced at a predetermined age or time. Barlow and Hunter [46] proposed a minimal repair model, where a system was replaced periodically at predetermined time and repaired upon its failure. The repair (minimal repair) brought the system back to its previous stage prior to its failure. In another word, the failure rates of the system before and after the minimal repair did not change. Probabilistically, the survival probability of the system after a minimal repair up to time $t+s$ was $\frac{1-F(t+s)}{1-F(t)}$ and the failure rate was $\lambda(t+s)$, where $F(t)$ was a failure distribution of the system, and $\lambda(x)$ was the failure rate [30, 47]. They showed that with a certain cost setup, there was an optimal age to replace a system yielding the minimal expected long run cost. The model in [46] was further generalized in [56, 267, 273, 335]. Abdel-Hameed [3] extended the model in [46] to include choices of maintenance actions at failures. They assumed that a decision maker could choose to perform either a minimal repair or a replacement with probability p and 1-p, respectively.

Kadi et al. [16] considered the problem where a decision maker could choose to replace a system with a used or less reliable system at a scheduled replacement time but performed a minimal repair at failures. Kadi and Cleroux [195] allowed a system to work while some components of the system failed, or let the system be idle and wait to be replaced in the next replacement period. They concluded that a system was replaced preventively with a new system in period kT. If the system failed between time $(k-1)T$ to $kT-\delta_1$, it was replaced with a new system (corrective maintenance). If the system failed between time $kT-\delta_1$ to $kT-\delta_2$, it was replaced with a used system, and if it failed between $kT-\delta_2$ to kT, the system would be left idle or work less effectively (the system was allowed to work, while some of its components failed) and waited to be replaced in the next replacement

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period *(k+1)T*.

Instead of finding the optimal replacement age T which minimized the expected cost, Kapur and Bhalla [196] found the optimal replacement age T which maximized the service reliability of a system. Several research, such as, in [66, 65, 78, 79, 114, 369] assumed that a cost associated with the minimal repair was not a constant. The works in [59, 57, 130, 174] proposed a cost control limit, where the system was replaced if the estimated repair cost exceeded a certain amount. However in their assumption, the system was repaired upon its failure, and no preventive maintenance was in consideration. Park [293] showed that there existed a closed form solution to find the cost threshold (repair limit), where a failure distribution followed a Weibull distribution, and a repaired cost distribution followed a Negative Exponential distribution. Nguyen and Murthy [279] later generalized this model and proposed a control limit where a system was replaced at time T or at cost x where x was a repair limit. They set up both a failure distribution and a repair cost distribution to follow Weibull distributions.

Tahara and Nishida [361] proposed a (t, T) model, where a system was minimally repaired if a failure occurred before time t, and it was replaced if a failure occurred between time t to T. If there was no failure occurring before T, the system was preventively replaced in period T. Muth [263] proposed a similar model to the model in [361]. However, Muth's model was easier, since its model had only one control limit T, where the system underwent a minimal repair if it failed before period T and was replaced at the first failure after period T.

A minimal repair model was improved further to an S-minimal repair (statistically minimal repair) model, where a failed component was restored to the exact physical condition before its failure, or an F-minimal repair model, where a failed system was replaced by a component which had exactly the same history but did not fail, [25]. It was shown in [25, 144, 276] that the statistically minimal repair (SMR) model led to a longer total life of the system than the F-minimal repair model (FMR), $\bar{F}_{SMR}(x) \geq \bar{F}_{FMR}(x)$, where $\bar{F}(x)$ was the distribution function of the remaining life of a system having a life distribution of $F(x)$.

The models discussed so far assume that a failure distribution of the system

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is known. However, the failure distribution is usually unknown in practice. Sathe and Hancock [321] used a Bayesian approach to find the optimal repair/replacement policy. Bassin [50] extended the model proposed in [46] to consider a system whose failure distribution was Weibull. Given a realization of failure times, he used Bayes' theorem to find a posterior shape and scale parameter of the Weibull distribution and found the optimal overhaul interval. Joshi and Gupta [193] used the failure history of equipment to add routine maintenance into production scheduling to prevent failures. Mazzuchi and Soyer [246] modeled a system whose failure distribution was a Weibull distribution and used Bayes' theorem to find a control limit of the block replacement with minimal repair policy and a control limit of the age replacement policy. Sheu et al. [341] extended the model in [246] by assuming that the repair cost was random.

2.2.1.3 Minimal Number of Failures Repair Models

The minimal repair models implicitly assume that the damage of a system is not cumulative. However in reality, the damage is accumulated even if the system is partially repaired. Thus, the minimal repair models do not accurately mimic a real system. Minimal number of failures repair models are proposed in order to improve this drawback. In the minimal number of failures repair models, a system is minimally repaired for the first $n-1$ failures, and it is replaced at the n^{th} failure [164, 234, 235, 236, 257, 269, 270, 278, 299]. Instead of replacing a system at the n^{th} failure, Park [292] proposed to replace at the n^{th} repair.

Sheu [336] considered two types of failures, a small failure and a catastrophic failure. He proposed that a system was replaced if a catastrophic failure occurred, but it was minimally repaired if a small failure occurred. The system was preventively replaced after k small failures. Park [292] showed that under a Weibull time to failure distribution and a constant repair cost, there existed a unique number of failures, n^*, and time, T^*, for this policy. The system was minimally repaired if the number of failures did not exceed n^*, and a failure time t was less than T^*, however, the system was replaced at the n^* failure or in period T^*, whichever occurred first.

Bai and Yun [38] proposed a model to find a repair limit of a system that

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had an increasing failure rate. Nakagawa [270] studied the traditional replacement models, such as, a block replacement model, an age replacement model, a periodic replacement model, and a minimum number of failures repair model under the assumption that a failure distribution followed a discrete distribution. The difference between the periodic replacement model and the block replacement model was that in the block replacement model, a system was replaced in period kT or at failures, whichever came first, but in the periodic replacement model, the system was replaced in period kT, but it was minimally repaired at failures. He proposed several combinations of the traditional replacement-repair models and found the control limits of the combined policies. Sheu et al. [340] extended the minimal repair model to consider two types of failure, a minor failure where a system was corrected by a minimal repair, and a major failure where a system was corrected by a replacement. They concluded that the system was replaced when it reached an age T, or at the n^{th} failure or at the first major failure, whichever occurred first. The model in [340] has been further expanded to include failures due to shocks in [339].

Previous models discussed in this subsection so far assume that a system is replaced in kT period, where k is a positive integer. In another word, if there is no failure, the system is replaced every T period. Nakagawa [271] modified this periodic preventive maintenance to a sequential preventive maintenance policy, where a preventive maintenance was performed in period x_k, where k=0,1,2,..., and a system was replaced after the N^{th} preventive maintenance. The difference between the periodic preventive maintenance model and the sequential preventive maintenance model was that inter preventive maintenance time is equal in periodic maintenance, while it may not be equal in the sequential preventive maintenance.

2.2.1.4 Repair Models with Age-dependent

Block et al. [75, 76] generalized a policy in [86] to consider a system's age, where the age of the system was measured during an inspection. They considered two maintenance actions upon failures i.e., a complete repair (replacement) or a minimal repair with probability $p(t)$ and 1-$p(t)$, respectively. If the minimal repair was performed, the failure process was a non-homogeneous Poisson process, but

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if a complete repair (replacement) was performed, the system then became a new system. As a result, successive perfect repair times were a renewal process. Sheu and Griffith [336, 338] extended this model from a univariate model to a multivariate model, where the effect of imperfect repair changed over time.

Chen and Feldman [100] assumed that operations cost depended on age of a system. Furthermore, they imposed that the system could be minimally repaired once, after that it would be replaced. They showed that the (t, T) policy was the optimal policy, where the system was minimally repaired if a failure occurred before time t, but it was replaced if a failure occurred between time t to T. If no failure occurred before T, the system was replaced in period T. This model was further generalized in Chen et al. [99] to include inspections.

2.2.1.5 Repair Models with Systems' Deterioration

In this subsection, we focus our interest on repair models, where a system deteriorates over time. Tatsuno et al. [365] modeled a deteriorating system using a Markov chain, where the stage of the Markov chain corresponded to the system's deterioration level. A failure occurred if the deterioration level exceeded j, where j was the threshold level. Maintenance actions, such as, an emergency replacement, a minimal repair and a preventive replacement, were chosen depending upon the stage of the system. They proposed an (i, I) policy, where the emergency replacement occurred at the first failure after stage I, and a minimal repair was performed if the deterioration level was less than i. A preventive replacement was performed if there was no failure occurring before stage I and the stage of the system was greater than i. Under some conditions, they showed that there was a unique optimal for i^* and I^* for this policy.

Milioni and Pliska [254, 255] developed a model for an optimal inspection schedule for a deteriorating system. They assumed that the deterioration process was a semi-Markov process which had three states, i.e., good, failure and deflective. The work by Ozekici and Papazyan [287] expanded the state of a semi-Markov process to any positive integers, where the system started from good states, progressed to deflective states and finally ended at failure state. Ozekici and Pliska [288]

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later extended previous research in [254, 255, 287] to add the case where the inspection did not provide perfect information. Yeh [391] proposed an approximation method to transform a semi-Markov maintenance model to Markov maintenance model, so that the analytical tractability of Markov process was preserved.

Bagai [37] modeled a deteriorating system where the deterioration process was a non-homogenous Poisson process. With certain assumptions, Bagai proposed that the system should never be replaced but minimally repaired at failures. Instead of finding an inspection schedule, Lam [390] proposed an algorithm to find the optimal number of inspections before the system was replaced. In his model, he assumed that an inspection was imperfect and the life of a system possessed an increasing failure rate distribution. Lam and Yeh [213] proposed an iterative algorithm to find optimal maintenance policies which minimized the expected long-run cost for continuous-time Markov deteriorating systems. They assumed that the deterioration level of the system was known only through inspections.

2.2.1.6 Repair Models under Shocks

This subsection discusses a repair model, where a system degrades only by shocks. Feldman [142] studied a system damaged only by shocks, where a shock process was a semi Markov process. Aven [32, 33] assumed that a shock process was a counting process and found a replacement period by finding a stopping time of a counting process. Nakagawa and Kijima [272] and Qian et al. [307] studied a policy, where a system was replaced at time T, at the N^{th} failure, or at a damage level Z, whichever occurred first, but it was minimally repaired when a shock occurred. Sheu [337] later extended the work in [340] to include shocks, where the arrival of shocks followed a non-homogeneous Poisson distribution. While several works focus on finding the optimal policy to minimize the expected cost, Wortman et al. [386] studied a maintenance policy which maximized the availability of a system. Their model was more suitable for a system which was exposed to an extreme event because only one shock could fail the system with high probability. They found that the availability of the system was increased if we eliminated sources of variability in the inspection, as a result a deterministic inspection strategy was optimal.

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A deteriorating system subjected to both shocks and aging process, where the deterioration of the system was known due to inspection, was studied in [214, 103, 104]. In these research, they assumed that the system failed only at shocks. The aging process only worsened the system but could not cause the system to fail. Their maintenance decision at each stage depended upon the previous maintenance action. Under some assumptions, they showed that the optimal control policy was to replace the system when a system was at a threshold stage j, which could be an age T, or time, whichever came first.

In contrast to other shock models, where a shock represents a damage to a system, Kijima and Nakagawa [201] viewed a shock as an improvement of the deterioration of a system. They proposed that each repair reduced the damage level by $100 \times b\%$, where $b \in [0, 1]$. If $b = 1$, it was a minimal repair, and if $b = 0$, it was a perfect repair.

2.2.1.7 Imperfect Repair Models

In the previous subsections, the studies are limited to only those that consider a replacement (perfect repair) and/or a minimal repair (repair to its previous stage prior to its failure). In this subsection, we focus on models with partial repairs or imperfect repairs (the recovery is between the perfect repair and the minimal repair). The partial repair or the imperfect repair restores a system partially. Eppen [136] assumed that a system degraded stochastically satisfying the Markovian property. In each inspection, a decision maker could decide to leave the system at stage i or perform a maintenance to restore the system to a better stage j, where $j > i$. Under some conditions, he showed that there existed a unique stage i^*, where a system was preventively maintained when it went beyond this stage.

Chan and Downs [97] introduced an imperfect repair model, where a preventive maintenance was repaired with probability p. Brown et al. [85] studied an age replacement model, where a system was replaced at a specified age and was partially repaired upon its failure. They assumed that a partial repair reduced the age of the system by a constant fraction. The repair was performed if a system reached an age T, or a failure occurred. They also assumed that the recovery value of partial

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repair was a linear function of the service age at a failure. The extensive review in the area of imperfect repair can be found in [298].

2.2.2 Condition Based Maintenance Models

Several models for CBM in the literature assume that the condition of a system is found by periodic inspections. After inspections, they assume to have perfect information of the condition of a system. Many models use a Markov model to find a control limit of a maintenance action (repair or replacement) [99, 158, 392]. Honzalez et al. [179] and Wijnmalen and Honzalez [380] considered a problem, where an inspection did not give perfect information about the condition of a system. Barbera et al. [44] studied a two-unit series model using a dynamic program to find an optimal maintenance action, i.e. repair only one unit or both units. Under an assumption of economy of scale and a cost setup, they showed that a repair of both units was the preferred maintenance action. Castanier et al. [94] developed a model followed the assumption that the condition of the system was known continuously, instead of periodically from the inspections.

Barata et al. [42] used Monte Carlo simulation to find a maintenance schedule. They assumed that failure occurred if the deterioration of components exceeded their maximum deterioration level. If a failure occurred, the component was replaced with an associated replacement cost. However, it was possible to repair a component before it failed with an associated repair cost. They proposed a search over the set of possible deteriorations of each component to find a threshold value for repair such that the expected long run cost was optimal.

Chiang and Yuan [103] modeled both a shock and an aging deterioration by using a Markov Chain. However, their system could go to failure stage only by a shock. The aging deterioration contributed only to worsen the condition of the system. They showed that it was optimal to replace a system upon failures or a system reaching a certain age.

2.2.2.1 Multi-Component System Repair Models

Previously, our main interest was in models for a single component system. This subsection reviews the repair models of multi-component systems.

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Nakagawa [268] considered a two-component system, where the system was replaced if component 2 failed or component 1 suffered k failures. In his model, he implicitly distinguished between components 1 and 2, where component 1 was more critical than component 2. Ohashi [284] assumed that a component deteriorated followed the Markovian property, and a decision maker could choose to do nothing, to replace a component or to minimally repair a system. He proposed that an ABC policy was an optimal policy, where a component was kept if the deterioration of the component was less than A. If the deterioration of a component was between A and C, the opportunistic replacement was performed. If the deterioration of a component was between B and C, the component was replaced if the system fails. If the deterioration of a component was greater than C, the operation was stopped, and we replaced the component immediately.

Sandve and Aven [318] extended a single-component minimal repair model to multi-component repair model. They argued that a Markov model was not practical because the equation used to solve the problem was too complex to solve. As a result, they solved the multi-component repair model by using the theory of monotone system [48] and proposed the following policies.

1. *T-policy*: the system (every component) was replaced in period T. This policy was more attractive if the component's failure cost dominated other costs, such as, the costs of system replacement and the system failure.

2. *(T,S)-policy*: the system was replaced at the first failure time, S or in period T ($T \leq S$), whichever came first. The *(T,S)-policy* was the best if the system failure cost dominated the costs of component's failures.

3. *R-policy*: the system was replaced depending on the condition of the system. Each time a component failed, a preventive replacement time was calculated. The system was replaced within this calculated period or the period in which the next component failure, whichever came first. This policy was the best if the system's failure cost was high.

Satow and Osaki [322] modeled a two-component unit model, where the process of component 1's failures followed a Poisson process, and the failure of component 1

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led to component 2's damage. In another word, Satow and Osaki's model addresses interactions between components. The system failed if the total damage exceeded a specified level. In their study, they set up two policies. The first policy was a one-parameter policy, where a system was replaced at an age T (policy 1a) or when the total damage exceeded a specified level K (policy 1b), while the second policy was a two-parameter policy, where a system was replaced at an age T or the total damage exceeded a specified level K, whichever occurred first. They showed that it was unnecessary that having more parameters led to lower expected cost unless a new parameter contained new information which was not contained in the old parameters. Castanier et.al. [93] also modeled a two-component unit model under condition based maintenance, where each unit was monitored by sequential inspections and its deterioration process was a continuous process.

In a traditional minimal repair model, a system was restored to a stage prior to the failure state (before-failure state). Aven and Jensen [35] claimed that the before-failure state was very different between a one-component system and a multi-component system. They generalized the minimal repair model to include both the information of every component in the system and the system's life distribution by using probability theory. Dickman et al. [127] studied opportunistic replacement as an integer program where a replacement was done during a regular scheduled maintenance. For the application of the maintenance scheduling problem in industries, the reader should see [23, 165, 183, 218, 388].

This subsection reviewed maintenance scheduling problems addressed in the literature. In summary, the maintenance scheduling problems find the trade-off between failures costs and preventive maintenance costs. Several researchers find the optimal time for the replacement of a product or a components at a pre-determined age or time. The literature on maintenance scheduling is important to this dissertation where it gives an overview of concepts, techniques and methods to find strategically optimal maintenance actions for the product on which an LTSA is extended.

While maintenance scheduling problems are similar to the operations management of LTSAs from product's perspective. Machine replacement problem addresses

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maintenance from part's perspective.

2.2.3 Machine Replacement Problem

In the context of machine replacement problems, we consider a replacement of a portfolio of machines or assets, while the replacement and the repair models in Section 2.2.1 deal with replacing a component in a machine. The replacement of assets poses a challenge to every engineering economist to find machines' optimum age, or when to replace existing machines (assets) or fleets by new machines or fleets. The replacement of old assets will lead to a better production plan, capital budgeting, and long-range planning.

The machine replacement problem has been studied extensively in the past by investigating the replacement, the maintenance, and the failure of assets or machines. The machine replacement problems can be divided into two categories, i.e., a serial replacement problem and a parallel replacement problem. The difference between these two problems is that the serial replacement problems are treated such that there are no economies of scale among the assets, while the parallel replacements consider the effect of economy of scale in replacing more than one asset.

2.2.3.1 Serial Replacement Analysis in Finite Horizon

Serial replacement problems can be traced back to early 1900. Taylor [367] determined the length of time to keep a machine by minimizing the unit cost of production, while Hotelling [182] maximized the net profit rather than minimized the cost. However, the early models did not take into account technology advances until Terborgh [368] implemented it in his model by formulating the operating costs as a linear-increasing function of age and the capital costs as a linear-decreasing function of age. He introduced the concept of "adverse minimum", where the adverse minimum was the ages of machines that minimized the cost function. His solution was derived from the assumption that existing machines (defenders) and new machines (challengers) had the same adverse minimum. In another word, machines had the same optimal age. Thus, he proposed to replace existing machines whenever the cost of new machines was lower than the cost of the existing ones. Alchain [18] added the productivity of challengers into the model, where the production rate of the

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challengers (new machines) improved linearly over time compared to their defenders (existing machines). Oakford [282] relaxed the linear assumption and considered the geometric changes in challenger's cash flow.

The dynamic programming technique was implemented in analyzing the serial replacement problem in [60]. Bellman assumed that the output and the scrap value were a decreasing function of age, while the upkeep cost was an increasing function of age. Dreyfus [129] generalized Bellman's work and considered the revenue and the upkeep cost as a function of time. He implemented the technological changes as an exponential function of machines' age. Ahmed [14] assumed that the revenues were identical for each asset and tried to minimize average annual cost of each asset. In his model, the variables could be age, mileage or mechanical condition, while the stage corresponded to the planning horizon.

Oakford et al. [283] implemented Wagner's dynamic program to find a replacement model that maximized the net present value of machines. Bector et al. [55] presented the serial replacement problem in a tableau form which was very practical and easy to work. Adil and Gill [9] realized the curse of dimensions in the dynamic programming approach. Therefore, they modeled the replacement problem as an assignment formulation, however, the assignment formulation also had a limitation in computational time, since the computational time increased as the size of the problem increased.

Several authors modeled a replacement problem by setting up total costs or revenues as a function of time or age. Solutions were obtained by using calculus method and simulation method. Clapham [113] studied the optimum life of an asset before being salvaged. The optimal life was found such that the sum of the capital depreciation payments and the maintenance cost was minimized. Drinkwater and Hastings [130] assumed that the average cost per asset decreased initially, but it rose when the asset became older. They proposed to find a solution by iteratively solving the repair limit equation. Christer and Goodbody [109] analyzed the effect of the high inflation in the model and defined total operation costs as a function of labor, minor repair, and major repair. They minimized the average discounted cost over two replacement cycles of machines (two-cycle replacement model).

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Christer and Waller [108] considered the effect of tax into the replacement problem. They performed the sensitivity analysis between analyzing different replacement cycles in the model i.e., a one-cycle-replacement model, a two-cycle-replacement model and an infinite-cycle-replacement model. Further studies of tax adjustment in the replacement problems can be found in [105, 190, 199, 224].

Sethi [327] applied control theory to find the optimal replacement cycle. He assumed that machines had a uniform cycle with identical preventive maintenance. Sethi and Morton [328] implemented both control theory and dynamic program to solve the replacement problem. They used the control theory to reduce the state space of the dynamic program by finding the arc cost of the dynamic program. The arc cost was the maximum present value of the net of return of machine bought in period n and salvage in some later period. After finding the arc cost, they used dynamic programming algorithm to find the optimal replacement period.

2.2.3.2 Serial Replacement Analysis in Infinite Horizon

The following authors consider infinite horizon replacement problems. The focus of the infinite replacement problem is to find a "forecast horizon" or an "equivalent finite horizon". The idea of both terms is to find a horizon time, T, such that after making a replacement decision, the replacement decision from period 1 to T remains the same for any horizon which is longer than T. The concern of infinite horizon replacement problems is whether there exists a "forecast horizon" or an "equivalent finite horizon".

Chand and Sethi [98] studied one machine with multiple challengers. They incorporated the technological advances of challengers to the model by assuming that the cost decreasing monotonically in time comparing to their predecessors. However, they did not include the inflation and machines' degradation. In order to find a "forecast horizon," they solved the problem by using a forward algorithm of the dynamic program. The forecast horizon existed under certain assumptions. Goldstien et al. [156] extended Sethi and Chand's work [98] by considering two machines with different technologies. Bylka [89] still considered one machine model that was similar to the work in [98] but added switching costs between technologies

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of machines to its model. Bean et al. [52] developed the work from Bean and Smith [53] and used a dynamic programming procedure to find the decision on replacing defenders by optimizing the net present value. The work from Bean and Smith [53] showed that an "equivalent finite horizon" existed if cumulative costs and revenues function were bounded by an exponential function which had a growth rate less than the interest rate.

Malcomson [237] added the obsolescence of equipments for infinite horizon into Terborgh's [368] and Brem's model [84]. He assumed that the operating cost of challengers was less than the defenders. With this assumption, it was possible that the problem had multiple optimal solutions. He derived a sequence of lower bounds and a sequence of upper bounds on the optimal life. Van Hilten [373] assumed that the holding cost of a machine was a constant and showed analytically that both sequences converged. Meyer [252] considered both the technological advances and fluctuating demands. Kusaka [212] studied the problem with a gradually technological advance and found an upper bound of the number of replacement. Nair and Hopp [265] modeled the problem as a Markov process and found the optimal replacement under technological advances. They assumed that there were two technologies over the infinite horizon, i.e., one which was in use now, and another one which would be available in the future.

2.2.3.3 Parallel Replacement

A parallel replacement problem considers a replacement of assets (machines), where they are economically related among others. Economic interdependency among assets exists for various reasons such as a customers' demand is a function of assets as a whole rather than an individual, or there exists an economy of scale in replacing more assets, or there is a budget constraint in a replacement of assets.

Vander Veen [374] realized the importance of a parallel replacement problem. He studied a replacement of a group of assets such that the demand was satisfied. His model was to maximize the net future value of assets' cash flow, where the cash flow was divided into a fixed cash flow and a variable cash flow depended on a

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level of utilization of assets. He approached the problem by modeling it as a mixed integer problem and proposed a heuristic to solve the problem.

Jones et al. [189] studied the parallel replacement problem under variable purchase costs because the assets were more discounted if they were purchased in bulk. They formulated the problem as a dynamic program. However, the dynamic program suffered from the curse of dimensionality. To reduce the state space, the authors grouped the assets using an age criteria, i.e., they were no assets with different ages in the same group. Using the age criteria, the authors developed two rules. The first rule stated that it was never optimal to split groups of assets, called Non Splitting Rule. The second rule stated that it was never optimal to replace groups of older assets before groups of new assets, referred as Older Cluster Rule. Tang and Tang [363] and Hopp et al. [180] further assumed that if the maintenance cost was not less than the decrease in the salvage value, then it was optimal to keep or replace all assets regardless of age, referred as All or Nothing Rule. Application of these rules resulted in smaller state space in the dynamic program. Hence, the problem can be solved more effectively. Chen [101] studied both finite and infinite horizon for the parallel replacement problem under various assumptions of a maintenance cost and a salvage cost. He used a shortest path method to solve the finite horizon problem, and a Bender's decomposition to solve the infinite horizon problem.

Karakabal et al. [197, 198] added a capital constraint in the parallel replacement problem. They formulated their problem as a network problem, where a node corresponded to periods and an arc corresponded to a cost between each node (each period). The problems were solved using Lagrangian relaxation, where the authors first relaxed a budget constraint and showed that the relaxation problem (subproblem) was a knapsack problem. After obtaining the solution from the subproblem, the solution was used in Multiplier Adjustment Method in order to improve the objective function.

Rajagopalan [308] examined a replacement problem which allowed an expansion and a disposal of machines corresponding to the changes of demand. He assumed that the assets had economy of scale in purchase cost. He showed that the

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model in its problem was similar to the model of an uncapacitated plant location problem, where locations in the plant location problem were the combination of purchased time and disposed time, and customer locations in the plant location problem were the combination of demand in each period.

Hartman [167] examined various economy models in the parallel replacement problem and considered the different options in the decision, such as, buy, lease and rebuild in the model. The problem was modeled as a network problem, where each option was viewed as a plane [168]. A demand constraint was added in the parallel replacement problem in [171, 169]. Under some restrictions of the parallel replacement problem with a demand constraint, He later showed in [166] that the problems had a uni-modular characteristic, therefore, solving a linear relaxation yielded the optimal integral solution.

Hartman and Ban [170] studied a serial-parallel replacement problem. They considered replacing machines in an integrated system, where the capacity of the system was considered to be the minimum capacity of machine in a serial configuration. They modeled their problem as an integer program and solved a linear relaxation to get the lower bound because the integer program was hard to solve to optimality.

An opportunistic replacement was studied by several researchers. Dickman et al. [127] studied an opportunistic maintenance problem for two machines by using an integer program, while Malcomson [237] used probability theory to solve it. Pullen and Thomas [306] considered a two-unit opportunistic replacement model, where joint replacement was performed when a machine failed. Berg [64] used the age of a machine as a trigger to find an opportunistic replacement. Zheng and Fard [396, 395] proposed an opportunistic replacement, where the opportunistic replacement occurred only in scheduled preventive replacement period. Zheng [394] proposed a (T, w) model, where a machine was replaced at failure or at time T. The opportunistic replacement was considered if there were other machines with their ages between $(T - w, T)$ in a replacement period. The advantage of this policy was that new machines whose age was less than w would not be replaced.

Several extensions of the parallel replacement problem have been studied ex-

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tensively in many industries, such as, in a fleet vehicle design and in a portfolio of medical equipments. Elton et al. [134] studied the differences of two replacement models which minimized 1.) the total average costs per annum and 2.) the present value of all future costs. They showed that the present worth model yielded longer replacement periods than the total average costs per annum model. They also concluded that the present worth model was more appropriate to solve the technological obsolescence problem. Wadhawan and Miller [378] used a fleet failure distribution to forecast the fleet replacement. They modeled their problem using a Markov Chain, where state probabilities were calculated from the failure distribution.

Jones and Zydiak [189] studied a fleet design problem, where they wanted to find how many replacement groups the fleet should have, how big the replacement groups should be and what age each replacement group should have. The authors showed that there was a steady state in the problem. At the steady state, each replacement group cycled over time, however, they found that there were some paradoxical results when applied the optimality criteria from [190]. Hartman [167] studied these paradoxical results and showed that the paradoxical results occurred because Jones and Zydiak [189] did not consider any start-up or opportunity cost, while the research in [190] assumed an opportunity cost in each replacement.

Scarf and Bouamra [324] used the two-cycle replacement model from Christer and Goodbody [109] to solve the fleet replacement problem. Waddle [377] studied a replacement of a fleet of vehicles. He viewed the problem as a network problem, where a node was defined by age and time, and arc represented a replacement decision, keep or replace. He used a dynamic programming algorithm to solve the problem. Vemuganti et al. [376] took another approach when they viewed the fleet replacement problem as a shortest path problem, where their nodes corresponded to time. The ages of vehicles were not taken into account because they grouped the machines by the age and used an average age in each group to determine whether the group should be replaced. One advantage in their model was that their model was a shortest path method, as a result an LP relaxation yielded the optimal solution. Christer and Scarf [107] studied the replacement problem in medical equipments. Since the medical equipments were subjective to individual use, they included the

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penalty function in their model to mimic the subjective consideration. For the case study and reviews of the machine replacement problems, the reader should consult [149, 245, 317, 356].

Besides finding the optimal maintenance parameters and strategy, the provider needs to manage the inventory supporting the delivery of LTSAs. Next section provides a review of relevant literature in the area of inventory pool.

2.2.4 Inventory Pooling Models

This subsection provides a review in the area of the inventory pooling problems. Sherbrooke [331] developed a METRIC model, where he assumed that at each site (factory or plant) the failure process was a compound Poisson. Once a part failed, there was a probability r that it was repaired in the factory, and a probability $1 - r$ that it would be shipped and repaired at a repair facility. Because of the low demand and high value nature of most repairable items, such as, aircraft engines, he concluded that a one for one $(S - 1, S)$ reorder policy was the optimal policy. While the METRIC model was an approximation method, Simon [343] and Shanker [329] found an exact solution of a two-echelon inventory problem under the assumption that repair time was deterministic.

Graves [159] argued that the METRIC model proposed by Sherbrooke in [331] underestimated the backorder costs of a plant. As a result, he proposed a new approximation model which used a Negative Binomial distribution to fit the distribution of backorder costs of the plant. However, his model overestimated the backorder costs and a new approximation model was, therefore, proposed in [332]. Lee [219] extended the METRIC model to include the transshipment between factories. While Lee's model focused on modeling the number of outstanding orders, Axsater's model [36] focused on modeling the demand at a factory. While the works in [219] and [36] were based on approximate method, an exact solution can be found in [385]. Sherbrooke [333] performed a simulation study to estimate the expected backorders in a multi-echelon system with lateral transshipment, while Ahmed et al. [13] solved the problem using simulated annealing technique.

Sleptchenko et al. [344] extended the VARI-METRIC model in [333] to include

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repair capacity. They showed that the infinite repair capacity may lead to errors in estimating system availability and errors in determining stock levels if the utilization of a repair shop was high, since the infinite repair capacity ignored the correlation of the backorders of various items. Van Harten and Sleptchenko [372] relaxed the repair facility constraint in [344] and assumed job priorities for repair. Sleptchenko et al. [345] combined these two features, i.e., finite repair capacity and job priorities, in the VARI-METRIC model.

De Haas and Verrijdt [124] used METRIC and MOD-METRIC models presented in [259, 331] to set a service level for repair and stock locations of repairable items. In their context, the service level corresponded to the percentage of demand of a part that can be met immediately from stock on hand. Alfredsson [19] studied multi-echelon repairable items with multiple repair facilities. He optimized the stock levels in each facility by minimizing the number of backorders. His model assumed that each repair facility had a $(S-1, S)$ policy, and the transshipment time from plant to repair was negligible. Alfredsson and Verrijdt [20] allowed direct shipments from an infinite supply when the total demand was not met, as a result their model did not include backorder. Barros and Ripley [49] added a discard option to the problem and used a branch and bound algorithm to find the optimal stock level in order to minimize the number of backorders. Instead of minimizing the expected total cost or a number of backorders, Almeida [21] proposed a model which minimized the utility function of system's interruption time. Jung et al. [194] expanded the lateral shipment transshipment model to include a finite capacity in a repair depot.

Several research, such as, in [20, 36, 219], assumed that a demand at a warehouse, which could not be supplied by its on-hand stock, was supplied by lateral transshipment from other sources, such as, other warehouses or buying new parts. Kukreja et al. [210] allowed stocks to be completely pooled among warehouses. Thus, the part's transshipment rule was based on the transshipment cost, but the transshipment time was assumed negligible. They developed a queuing model to solve the problem and concluded that organizations with a number of plants, warehouses or stocking points earned a benefit from the uses of lateral transshipment. Tuataras and Cohen [359] used simulation technique to evaluate the performance

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of several transshipment policies, such as, complete pooling, partial pooling. They concluded that the complete-pooling strategy always dominates the partial-pooling strategy.

Tuataras and Vlachos [360] relaxed the transshipment time assumption and showed via simulation that the benefit of pooling was substantial only if a demand was highly variable. Grahovac and Chakravarty [157] implicitly considered the transshipment time by assuming that the manufacturer's lead time depended on geographical distance and set up a system in which inventory flowed from a manufacturer to retailers/customers via a distribution center. Wont et al. [384] allowed some delay in lateral transhipment. They developed an approximation method by using a Markov model to solve the problem and concluded that the delayed lateral transshipment reduced the expected number of backorders.

2.3 Conclusions

This chapter provide an overview of literature pertinent to our research. The service delivery of LTSAs combines several features of many problems such as product designs, maintenance scheduling, and inventory management. These problems have been studied extensively and separately in the literature, however, none of the research directly addresses issues specific to management of LTSAs. Therefore, while we will take advantage of the advancements in these fields, more original work and analysis of maintenance analysis, replacement scheduling and risk assessment and management are required for LTSAs. These analyses is developed in the following chapters.

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CHAPTER 3
Anatomy of risks in the Service Delivery of Long-Term Service Agreements

Long-term service agreements combine several features of many problems, such as, service operations management, maintenance management, scheduling management, inventory management, and financial management. These problems are very well known and are studied extensively in the literature. However, these problems are often addressed separately from each other. Our dissertation attempts to bridge these different disciplines through the perspective of risk management and assessment framework. The objective of the dissertation is to develop an effective risk mitigation strategy for properly managing risks of the service delivery of LTSAs. In this chapter and following three chapters, we will develop a risk assessment and management framework to find an optimal service delivery strategy as well as an optimal financial strategy for the provider. This chapter begins the analysis of risks by identifying sources of risks in the service delivery.

3.1 Introduction

LTSAs are usually aimed to give a customer assurance and/or ease of use of a product over a contract period running up to decades. Since the customer usually has little knowledge about the product compared to the provider, LTSAs offer a risk sharing between the customer and the provider. The customer hedges the risks of operating and maintaining the product by transferring the responsibility for maintaining the product to the provider, while the provider capitalizes on its knowledge of the product to gain profit by providing necessary services for the customer.

Risks are very important to the provider. Risks the provider are exposed to fall into three categories, i.e., strategic risk, operational risk, and extreme event risk. Strategic risk pertains to long-term decisions, while operational risk relates to short-term or tactical decisions. An extreme event risk is a risk due to a rare

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event. In order to manage these risks efficiently, the provider needs to assess them and develop an integrated risk management plan.

One method which helps the provider develop an integrated risk management plan is to use a systematic risk assessment and management process. The risk assessment and management process helps the provider better analyze its risk exposures, mitigate them systematically, and manage them efficiently. The risk assessment and management process constitutes of 5 steps as follows [163].

1. Risk identification is the first and a major step where we identify sources and nature of risks and uncertainty associated with products and the service delivery process.

2. Risk measurement is used to assess and quantify the likelihood of risks through an objective and/or subjective probability.

3. Risk evaluation is used to evaluate risks corresponding to the provider's objectives. In this step, the provider develops several strategies and finds the trade-off among these strategies.

4. Risk avoidance and acceptance is a decision making step. A decision is to determine the level of acceptability of risk based on trade-offs evaluated during the risk evaluation step.

5. Risk management is an execution step where the provider implements their decisions to detect, prevent, control, and manage risks. The feedback received upon an execution is fed to the risk identification step to improve the quality of risk model and risk management, as shown in Figure 3.1.

This chapter discusses the first step of the risk assessment and management process, where sources of the risks of the service delivery of LTSAs are identified. Next section dissects sources of risks in detailed.

3.2 Dimensions of Risks in the Service Delivery of LTSAs

This section identifies general setup and risk factors of the service delivery of LTSAs. The general setup is aimed to help the provider better comprehend chal-

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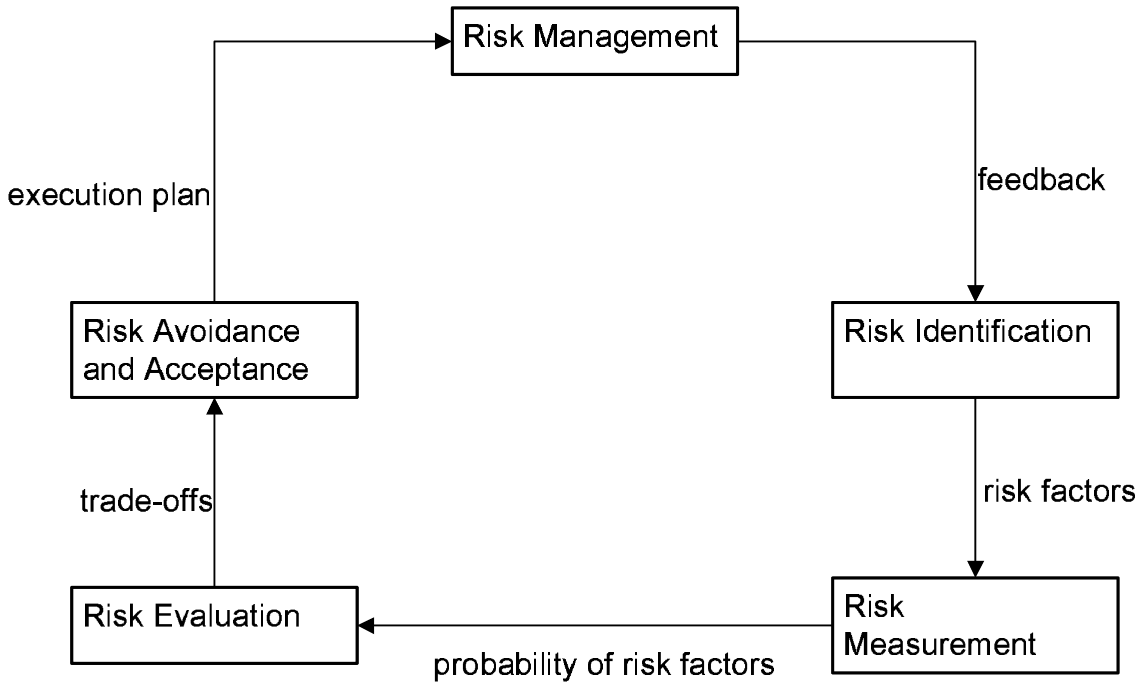

Figure 3.1: Risk assessment and risk management process

lenges and risks of LTSAs. The setup is divided into nine categories as shown in Figure 3.2. The setup includes product design, product manufacturing and/or installation, contract specification, physical service infrastructure, knowledge-based infrastructure and management, sales and marketing, financial resource management, government regulations, and legal issues. Among the general setup, product design, product manufacturing and/or installation, service infrastructure, and knowledge-based infrastructure and management directly affect the contract setup and specification or the service design of the delivery of LTSAs. It should be noted that contract setup and specification influence the service design, since the provider is required to deliver its service as written in the contract. While financial resource management and sale and marketing can be viewed as endogenous risk factors, government regulation and legal issues are exogenous sources of risks to the provider.

3.2.1 Product Design

The delivery of LTSAs begins with product design, where the provider (manufacturer) needs to design a product such that it is the most reliable, econom-

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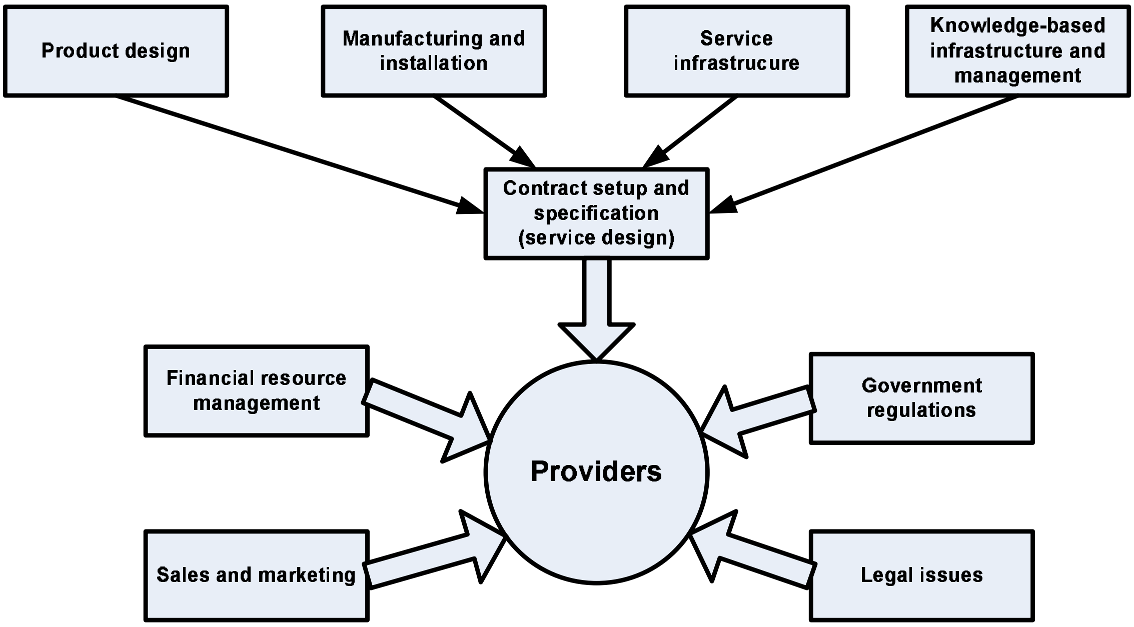

Figure 3.2: The relationship between setups and provider

ical, serviceable and durable, easy to maintain and operate, and more recently eco-friendly and efficient [118]. Product design is a decision-making process which balances between customer's needs, functional requirements, and economical constraints [290, 238]. The process enables the provider to develop the most effective and efficient product with the lowest cost.

Product design relates to both operational risks and strategic risks of the delivery of LTSAs. Product design relates to operational risks because decisions during this stage are varied from customer to customer due to the nature of customer's usage of the product, communications and interactions between the customer and the provider.

The product design also pertains to strategic risks because several decisions made during the product design process are used for a design of the service delivery process at later stage. For example, the operational protocols of the service delivery, such as, maintenance actions, are created based on the product reliability and prototype testing. The product design process can considerably reduce maintenance needs for a product over its life cycle [238].

Even though the risks of product design can be reduced through iterative de-

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signs and testing, the risks cannot be totally eliminated. The provider is exposed to the risks due to premature prototype, high product design cost, product modification requested by the customer, and design quality, i.e., poor technical executions, and future technology. The main contribution to these risks includes product complexity, technological requirements and difficulties, and the provider's product and process development capability [12].

The risks of product design can be reduced through iterative designs and testings. Moreover, the provider needs to encourage communications with its customers, since the customers are product users and co-produce maintenance with the provider. The provider would want to streamline customer's comments, suggestions, and requirements to product modifications and revisions in order to achieve a mature design with minimal costs.

3.2.2 Manufacturing and Installation

Followed the product design, product manufacturing and installation pertains to processes transforming a paper-based design to be a ready-to-use product. Product design and product manufacturing and installation are important since major failures can be traced back to the design and manufacturing and installation phase [238].

The risks of product manufacturing can be divided into two parts. The first part involves the construction of a product. The building of a product pertains to strategic risks, since it mostly relates to the quality of a manufactured product. As a result, it can affect the performance of the product and its service delivery. The poor product quality can be caused by human errors, poor construction process, and material and machines used to produce a product. The second part relates to the manufacturing process. The risks of manufacturing process include manufacturing deadline, expenses during the product manufacturing, resource planning, and job scheduling. As a result, the second part mostly relates to the operational risks, since it concerns short-term decisions and are varied on daily basis. The major sources of the risks of manufacturing process consist of poor production management, poor supply chain management, and poor resources management. Risks can be increased

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if the provider opts to outsource some of its manufacturing process to third parties. These risks include poor quality threshold and loss of cross-functional contact and confidentiality [63, 256].

The installation risks relate to risks during an installation process. The installation risks pertain to operational risks because the installation process varies from a customer to a customer and relates only to short-term decisions. The provider is exposed to the installation risks where the provider may damage the product during the installation process. Three main factors contributing to the installation risks are human errors, installation equipments, and surrounding environment.

3.2.3 Contract Setup and Specification (Service Design)

LTSAs are well-crafted contracts between a provider and a customer. Contracts are usually complex due to the nature of sophisticated, high-cost, and long-lived products. Therefore, the provider and the customer co-create a contract in order to clearly identify and define their roles and responsibilities in the service delivery. In general, a contract covers financial obligations, engineering and functional deliveries, and legal bindings. The financial obligation and also penalty fee structures concern the price and the payment plan for a contract. The engineering and functional deliveries define the term ‘functionality’ of a product for the provider and the customer. In general, the functionality of the product can be measured in terms of performance measures, e.g., availability and throughput. Engineering and functional deliveries also specify operations and maintenance protocols and constraints for the customer and the provider. The legal bindings define contract duration, effective date, liabilities of both parties, extreme-event clauses, and other related legal issues.

The service design, in the context of LTSAs, mainly pertains to the delivery of the functionality of a product as well as its preventive maintenance for the customer. To maximize the functionality, the provider needs to aggressively adopt a preventive maintenance strategy, e.g., usage based, condition based, or a combination of several strategies. The maintenance strategy should be selected such that it is the most cost efficiency where the best trade-off between failure costs, costs of maintenance, and

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penalty fees is achieved.

The contract setup and specification affect the operational and the strategic plans, since the contract setup and specification relate to long-term decisions as well as vary from customer to customer. The strategic risks concern the long-term decisions, e.g., maintenance strategy and how the provider conducts its business, while the operational risks concern a daily tactical operations, such as, maintenance actions.

The risk factors of the contract setup and specification can be categorized into two types, endogenous factors and exogenous factors. The endogenous risk factors correspond to the performance of a product, e.g., interactions between components and the condition of components and a product. Risks occurred in product design, manufacturing and installation phases directly affect the service design because errors occurred during product design, manufacturing and installation directly impact the service delivery of a product. The exogenous factors pertain to any outside factors affecting the performance of a product, e.g., human errors, service infrastructure, and surrounding environment.

3.2.4 Physical Service Infrastructure

Elaborate and sophisticated service infrastructure is used to support the delivery of LTSAs. The physical service infrastructure includes monitoring systems, personnel, i.e., control and repair crews, spare part, repair facilities, and warehouses. In this dissertation, we mainly focus on monitoring systems and spare part inventory because they impact the service delivery the most. While the monitoring system helps the provider detect suspicious conditions leading to failures, spare part inventory assists the provider in bringing the product back to working stage.

The monitoring units as seen in Figure 3.3 are used to assess the condition of products. The monitoring system composes of three main components, i.e., sensors, data transmission system, and control center. Sensors are usually embedded in a product and capture data relevant to the assessment of the condition of a product. The data can be, for example, pressure, temperature, and vibration. After the data is captured, the transmission system relays these data to the control center, where

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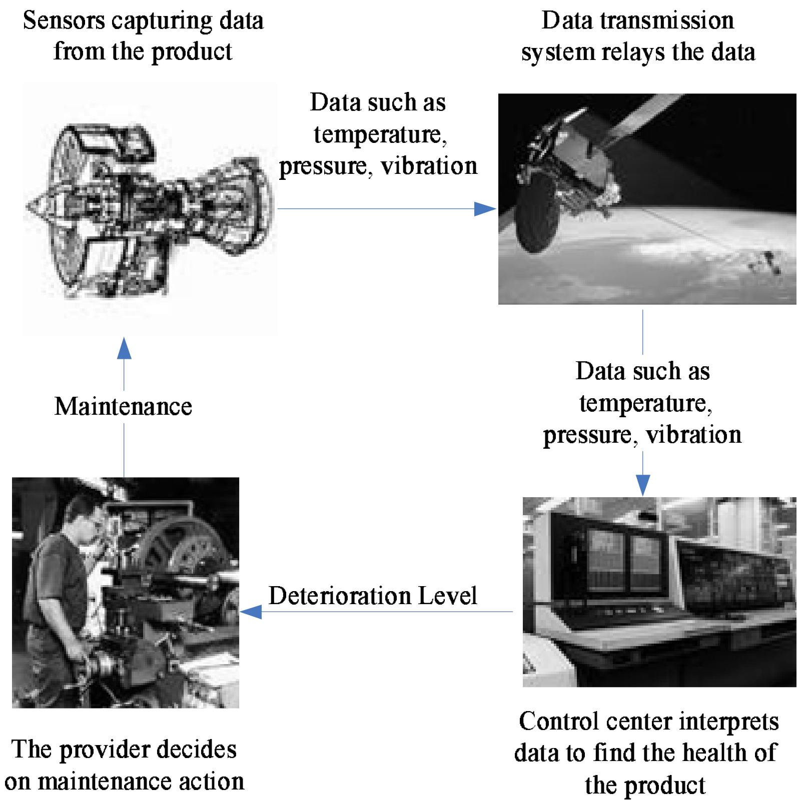

Figure 3.3: Process of monitoring systems

it assesses and translates these data into a meaningful condition or a deterioration level of the product and makes maintenance decision based on the assessed condition of the product for the provider.

The risks of the monitoring system relate to both strategic and operational level. On the strategic level, the provider needs to design the technology used in the monitoring system. On the operational level, the provider is exposed to the risks of data misinterpretation and data misuses [296]. The operational risks of the monitoring system correspond to statistical type I or type II errors. Type I error is when the monitoring system interprets the condition of the product as good, but it in fact is not. Hence, the true condition of the product is worse than it is perceived. Type I error can be caused by several factors, such as, errors in sensors, algorithmic errors in the control center, delays in data transmissions, and delays in responses to problems. On the contrary, type II error is when the monitoring system interprets the condition of the product is bad but it in fact is good. As a result, the actual

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condition of the product is better than the perceived condition. Several factors can contribute to type II errors, for example, incorrect data due to sensor errors or algorithmic errors.

The other infrastructure issues, such as, the number of spare part, repair crews, warehouses, and repair facilities are also a concern, since these issues relate to the availability of the products [11, 131]. The risks of these issues relate to both strategic and operational risks. The strategic risks relate to the decision on the location of repair facilities and warehouses, the facility design in repair facilities and warehouses, and the optimal inventory of spare part and other resources. The operational risks pertain to tactical management of repair facilities, warehouses, inventory, and resources in order to deliver the service faster and minimize costs.

3.2.5 Knowledge-based Infrastructure and Management

Similar to physical service infrastructure, knowledge-based infrastructure plays a crucial role in supporting the delivery of LTSAs. In our definition, the knowledge-based infrastructure constitutes all the technical and management know-how that ties product design, manufacturing, installation, physical service infrastructure, and service delivery. The provider utilizes its knowledge-based infrastructure in order to efficiently and effectively manage a portfolio of LTSAs. For instance, the provider utilizes its knowledge of product's reliability during the design stage and the data from the monitoring system to create a maintenance model. The maintenance model can be usage based, condition based, opportunity based, or a combination of these policies in order to minimize the number of failures [45, 128, 230, 319, 334, 355]. One method which tries to balance among these maintenance activities is to carefully select threshold levels based on data analysis of product's reliability and historical data such that the threshold levels conform to usage based maintenance program and periodic maintenance program, since some government regulations specify preventive maintenance in term of usage based [258]. Once the models are created, the provider can quantitatively analyze its long-term strategic maintenance and evaluate its efficiency as discussed in Chapter 5.

In order to efficiently manage the delivery of LTSAs, the provider needs to

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create planning and scheduling models to schedule production, repair and control crew, maintenance, and repair facilities. These plans and schedules complement the operations of the delivery process. In addition to these planning and scheduling models, inventory models for spare part are developed to avoid shortage and extra spare part in the warehouses.

Information system (IS) helps the provider manage its service delivery more effectively. IS plays a key role in transporting, managing, and storing data and information. They are used to collect and relay data from monitoring units to the provider's control facility [264]. Interfacing with IS, an expert system (ES) analyzes data, draws conclusions, provides recommendation for actions, and/or makes a decision for the provider. Moreover, IS is used to support the information flow in the supply chain and is used as a database for collecting, organizing, and storing information for a portfolio of contracts. Additionally, the provider should continue to provide a training to their personnel and customer's personnel in order to handle new technology and to improve the quality of the service delivery.

We can categorize the risks of knowledge-based infrastructure and management into three types, i.e., model risks, risks from IS and ES, and risks of poor training practices. The model risks relate to risks of using and creating incorrect or incomplete models. The modeling risks occur when modelers do not have complete understanding of the system they model. The risks of information systems and expert systems pertain to the reliability and fault tolerance of IS and ES. Since IS and ES are computer programs, they are prone to failures due to programming errors. Therefore, the provider is exposed to the situation that IS and ES do not perform their expected task. The provider should also have alternative plans to deliver the service when IS and ES are down. The risks of training concern human error during the service delivery process, where the personnel are wrongly or inadequately trained, or there are miscommunications between trainers and trainees during the training process.

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3.2.6 Sales and Marketing

Sales and marketing department is in charge of marketing campaigns and selling LTSAs to customers. Even though LTSAs provide several benefits for customers and providers, the benefits of LTSAs cannot be fully achieved if the sales and marketing personnel do not fully understand the nature of the products and the risks of LTSAs. Thus, the provider needs to create a guideline or a checklist for their sale units for selling LTSAs. Sale personnel may need to consult attorneys regarding the legal issues of the contract and engineers regarding the engineering specification and function of the products. Risks occur when salespersons do not fully understand the risks of LTSAs. Nevertheless, they manage to sell contracts to customers, since it is imperative to increase their sale volume. This is called a moral hazard problem where the salesperson who causes risky sales does not fully suffer the consequences of the risky sales or may, in some cases, actually benefit from the risky sales. The risks may occur if guidelines provided to them are weak, or the sale persons do not follow the guideline strictly.

Another important issue for sales and marketing department is time to market a product. For a very competitive business, time to market a product is very important. Customers always look for better, more efficient, more economical, and more reliable products. Hence the provider needs to aware of new technologies in the market and the advancement of its competitors in order to effectively introduce its new product to the market. It should be noted that effectively launching new products to the market is a very delicate decision process, where it concerns the technology available in the market, new products developed by the competitors, and the perception of customers [83].

3.2.7 Financial Resource Management

The financial resources are vital to the profit of the provider. In general, the financial resource management concerns cash flow risks of the provider. Financial resource management begins with pricing models. In general, the pricing models take into account type and model of products, contract duration, the initial age of the product, customer's site environment, performance measures and matrices

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to deliver. Upon an agreement between the customer and the provider, a payment plan is created to suit both parties. According to pricing models and payment plans, the revenue model is generated. The revenue model leads to an estimation of the profit of a contract and plans a long-term investment to hedge shortfall risks of the contract. The pricing models, the payment plans, and the investment analysis affect the provider's risk exposure. A loss-reserve estimation and a risk mitigation model should be created at the instant level as well as the portfolio level to ensure minimal financial risks for the provider. Purchasing insurance is one of the hedging strategy, where the provider transfers the cost of unforeseen risks, e.g., extreme-event risks, to insurance companies.

Financial risks relate to strategic risks. The financial risk factors concern both macroeconomic and microeconomic factors. The provider does not have a control over the macroeconomic factors, e.g., interest rate, inflation, fuel price, and foreign exchange rates. Underestimating or overestimating the macroeconomic factors affects the price of a contract calculated from the pricing model and the investment analysis. This is because macroeconomic factors are often parameters in these models. As a result, the provider may not be able to get the expected level of the profit.

The microeconomic factors concern the shortfall of the provider's expected return. Hence, they relate to structuring a portfolio, balancing the portfolio, and hedging strategies. The provider can control or partially control some variables in the risk factors, such as, price of contracts and its payment plan, contracts' duration, effective date, pooling of contracts, asset liability matching, insurance and re-insurance, and capital investment for short-term and long-term. The goal of the provider is to create a portfolio such that a revenue stream of the portfolio matches expenses of the portfolio (asset liability matching). Some factors cannot be controlled by the provider, e.g., customer default risks and risks of delayed payment.

3.2.8 Government Regulations

Several products sold under LTSAs support basic infrastructure of a country, such as, gas turbines, aircraft engines, locomotive engines, and medical equipments.

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The government, therefore, plays an essential role to ensure safety of consumers of the products. Regulations are imposed to ensure safety and/or address economic concerns for end-consumers [172, 178, 326]. The government can issue new regulations, change regulations, or discard old regulations. The provider is exposed to these risks throughout the contract duration, since the provider must create its operational protocols to match regulations issued by the government. For instance, the provider's maintenance plan of an aircraft engine must conform to the safety regulations required by the FAA. Besides the safety issues, the regulation can aim to prevail the competition in the industry, e.g., electricity industry. The changes in regulation may result in a decline of capital investment [72]. In case of regulation concerning economic issues, companies may need to restructure their business process and/or strategy in order to stay competitive [247]. The risks of changes in regulations pertain to strategic and operational risks, since the maintenance strategy and operational protocols need modifications responding to regulations by modifying its maintenance strategy from a strategic risk point of view and adjusting their operations to conform to the regulations from an operational risk point of view. In some cases, these risks can be transferred back to the customer via a renegotiation clauses written in the contract.

3.2.9 Legal Issues

Even though the provider interacts mostly with its customers, the providers may interact directly with end-consumers through legal issues. Consider the case where a failure occurs because of the provider's negligence. The end-consumers can directly sue the provider for their losses due to the negligence. In addition to the legal issues with the end-consumers and the customers, the government can take action in legal issues against the provider. Reported in Air Safety Week on March 15th, 2004, an accident of a Lufthansa jet in 2004 reflected shortcomings in government oversight, operator oversight of outsourced maintenance, clarity of the maintenance manuals, and functional checks of critical flight controls following maintenance. Legal risks relate to legal actions against the provider. The provider may seek to settle legal issues out off court or in court. In court the provider is ex-

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posed to the risks of an adverse judgement which may result in higher compensation than the settlement. The legal issues relate to an extreme-event risk.

The general setup and corresponding risk factors serve as a guideline for identifying risks for the provider. After thoroughly scrutinizing risks and understanding their nature, the provider needs to evaluate the risks and tries to develop a coherent risk management and service delivery strategy which systematically and efficiently mitigates the risks at a single and a portfolio level. The quantitative risk assessment and management framework will be developed in the following chapters.

3.3 Conclusions

LTSAs have become more popular, and several studies have shown several benefits of LTSAs. However, there is not much research addressing the risks of the service delivery. Without thoroughly understanding risks of the service delivery, the provider can be exposed to extensive losses and endanger product's end-consumers. In this chapter, the first step of risk assessment and management process is achieved where potential sources of the risks of the service delivery of LTSAs are identified and studied.

The risks of the delivery of LTSAs can be divided into nine categories, i.e., product design, product manufacturing and installation, physical service infrastructure, knowledge-based infrastructure, service design or contract setup and specification, financial resource management, sales and marketing, government regulations, and legal issues. Product design, product manufacturing and installation, physical service infrastructure and knowledge-based infrastructure directly affect the design of the service delivery, since the service design is created based on the interrelation between these issues and risks occurred at these categories directly affect the risks of the service delivery. Financial resource management and sale and marketing can be viewed as endogenous sources of risks, while government regulations and legal issues are exogenous sources of risks.

From these nine categories, we can broadly group them into four classes, i.e., product risks, service risks, financial risks, and extreme-event risks. Product risks concern risks that occur because of poor product quality. As a result, they in-

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clude product design and product manufacturing and installation. Service risks take into account risks which happen during the service provision. They involve contract setup and specification, physical service infrastructure and knowledge-based infrastructure. Financial risks refer to risks of cash flow. Thus sales and marketing and financial resource management directly affect financial risks. Lastly government regulations and legal issues are considered as extreme-event risks because they are unlikely to happen.

Every risk factor directly affects the service delivery of LTSAs. It is, however, prohibitively difficult to address every risk factor in a risk model and to solve the model in a timely manner. Following chapters will focus on the most important sources of risks where we develop a quantitative risk assessment and management framework. Next chapter will build a foundation of a quantitative analysis of risk management of LTSAs by considering only product risks.

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CHAPTER 4
Designing Optimal Service Maintenance Strategy of Monitoring-Enabled Multi-Component Systems from Product Risk Perspective

We have dissected risks affecting the service delivery of LTSAs in Chapter 3. Causes of each risk dimension are varied but sometimes interrelated. We would want to take advantage of the interrelations between different kinds of risks in order to mitigate them systematically and effectively. This chapter offers a stepping-stone toward a bigger picture of risk analysis where we develop strategic business management only from product risk viewpoint.

The dissertation concentrates on the service part of the delivery of LTSAs. The objective is to develop optimal strategic plans for the service delivery. The strategic plans include strategic business management and strategic operational management. Strategic business management pertains to long-term business decisions, where the plans for the service delivery of LTSAs are developed. Strategic operational management relates to long-term operational decisions, where the provider streamlines operational decisions to align with its business management strategy.

This chapter begins the first quantitative analysis of strategic business management problem, where we develop a strategic management for maintenance actions for a single product (system) by focusing only on product risks. The analysis of a single product is very essential, since it provides an understanding of the character of an individual LTSA. In particular, this chapter focuses only on risks related to the product where we assume that there is no risk incurred in the service delivery process. Therefore, this chapter is based on the assumption that all information and the process of the service delivery are perfect. As a result, this chapter will lay a solid foundation for the development of risk assessment and management for a single as well as a portfolio of LTSAs. It should be noted that in our context products and systems have the same meaning and, thus, are used interchangeably.

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4.1 Problem Background and Motivations

Efficient usage of high-tech, costly industrial equipment (product) requires not only a good operations schedule, but also a well-designed maintenance schedule. Once a product is installed at a customer site, the provider needs to monitor its performance and perform diagnostic and prognostic inspections in order to assess the condition of the product. Condition based maintenance (CBM) is widely implemented by the provider to assess the condition or the health of the product, since the provider can better estimate the condition of the product and make better maintenance decisions from real-time information provided by CBM. Moreover, CBM can save maintenance costs for a compony over 50-80% and improve profits of a plant by 20-60% [310]. With CBM widely used in practice, we develop our analysis based on the context of CBM in order to find strategic maintenance actions for a monitoring-enabled multi-component product (system) using continuous-time deterioration models with jumps.

A product (system) deteriorates over time due to aging, fatigue, usage, environmental conditions, or extreme events. After undergoing a certain level of deterioration, a system is increasingly likely to fail. In order to model and predict these failures, the condition of a system is assessed and summarized using a quantity that serves as an abstraction to capture the health status or the quantified deterioration of a system. With a view toward utilizing a CBM paradigm, the health of a system (and its components) is measured using observable quantities concerning the system's functionality, such as temperature, vibration, pressure, crack length, etc. These data are assumed available to facilitate measurement of the deterioration level of a system. Using the measured deterioration of a system, a decision maker can make a better maintenance decision of the system such as to continue to use, to repair, or to replace a system or its component(s).

In this chapter, trigger events are identified corresponding to deterioration levels for a multi-component system. Components may require somewhat different interpretation in different contexts. When a system is very complex, it may have thousands of parts, therefore, capturing all of them as components into our model will be prohibitively hard. As a modeling abstraction, it is critical to decide what

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level of components or subsystems resolution is kept in a model such that the model is not too complicated, yet good at mimicking the real system. In our context, a component means a module of a system that is essential for the system's functionality whose deterioration affects system performance significantly, and therefore needs to be incorporated into the model. A maintenance action is considered if the deterioration level of the system or its components fall in specified trigger zones. Failure Modes and Effects Analysis (FMEA) is used to derive the interrelation of deterioration levels of components and their impact on the system's deterioration. Maintenance actions are analyzed in order to maximize the system's functionality while controlling system's deterioration level that makes it susceptible to breakdown.

The chapter is organized as follows. Section 4.2 describes a single component system, followed by a generalization to a multiple component system. A maintenance model is discussed in Section 4.3. Section 4.4 describes the simulation method employed to find the deterioration of the system and elucidates the optimal maintenance search procedure. Numerical examples are presented in Section 4.5, followed by the conclusions in Section 4.6.

From the literature review in Chapter 2, we can conclude that not much research has used a continuous-time model to analyze system reliability and maintenance schedule, even though the condition of a product is continuously observed and monitored in sensor-enabled CBM. A continuous simulation, therefore, gives more insightful information that is consistent with the CBM paradigm than a discrete simulation, since a functioning product indeed deteriorates continuously with time. Moreover, an accompanying critical parts analysis, which determines the parts to be repaired and/or replaced such that long-term reliability of a system is optimized, is so far not studied.

4.2 A Multi-Component Deterioration Model

We begin this section by discussing the quantification of deterioration of a system captured in a continuous-time deterioration model with jumps. We start with developing the concept of measured deterioration (D) and a model for deterioration of a single-component system.

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The deterioration model captures the evolution of measured deterioration of a system over time. This measured deterioration is constructed in terms of information provided by CBM concerning the functionality of the system, such as, temperature, vibration, pressure, crack length, etc. The precise construction is a system-specific effort and is beyond the scope of this research. We assume that these sensor-measured quantities can be transformed using appropriate representation (F) to depict the health of the system (D) [151, 152].

$$F : (Y_{1t}, Y_{2t}, \ldots, Y_{nt}) \rightarrow D_t, \tag{4.1}$$

where Y_{it} are observations from the system (or its components) of quantities, such as, temperature, vibration, crack length, etc, under CBM. D_t is the deterioration level of the system at time, t.

4.2.1 A Continuous Deterioration Model

Consider a system with only one component that degrades randomly and continuously over time. The degradation of the system lies between D^0 and D^{max}, where D^0 is the perfectly fit deterioration level of the system, while D^{max} is the maximum deterioration allowed for the system. The system fails if its deterioration level exceeds D^{max}.

Several models have been proposed to study a single-component system subject to deterioration due to aging. For example, a Fatigue Crack Growth model studies the crack growth of a system to predict the life of structures [351, 350, 362]. Grall et al. [158] proposed a model assuming that the deterioration process satisfies the Markov property. This is further generalized in [112] where the increment of the deterioration level is given by,

$$\Delta D_t = \alpha(D_t, t)\Delta t + \beta(D_t, t)\Delta X_t, \tag{4.2}$$

where ΔD_t is the increment in deterioration in time (Δt), and ΔX_t is the increment in an appropriately chosen stochastic process. $\alpha(D_t, t)$ is the deterministic rate of increase term, called the drift coefficient, and $\beta(D_t, t)$ is the variability coeffi-

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cient, termed as the diffusion coefficient. Specific forms for these functions, $\alpha(D_t, t)$ and $\beta(D_t, t)$, will need to be chosen based on the properties of the system. The parameters in these coefficients will in general be estimated from observations of a system's deterioration process, or from the engineering design analysis or reliability tests data. X_t can be chosen to be the Wiener process, Ornstein-Uhlenbeck process, and Poisson process [42, 112, 350].

For some choices of X_t process, such as, for the Weiner process, by Equation 4.2, it is possible that the deterioration of the system decreases with time because ΔD_t can be negative. We, thus, modify Equation 4.2 so that the deterioration of the system is a non-decreasing function of time as follows:

$$\Delta Z_t = \alpha(Z_{t-1}, t)\Delta t + \beta(Z_{t-1}, t)\Delta W_t, \tag{4.3}$$

$$\Delta D_t = f(Z_t)\Delta t, \tag{4.4}$$

where Z_t is an Ito process, and W_t is the Weiner process. The function, $f(\bullet)$, can be any positive, integrable function, such as, the exponential function, an absolute value, a square function, etc. This transformed model is referred to as a two-stage model [350, 362].

4.2.1.1 Jumps in a Single Component Deterioration Model

A jump in deterioration can be used to capture either an extreme event or a non-extreme jump event. An extreme event is a rarely occurring event that yields a severe damage to a system. A non-extreme event is an event that occurs more frequently but does not yield as much damage as an extreme event. We model the arrival of a jump using a Poisson process. Assuming only one shock can occur in an arbitrarily small period of time, jump in deterioration can be described as follows.

$$J_t = U_t \times I_{\{N(t^+)-N(t^-)=1\}}, \tag{4.5}$$

where $I_{\{N(t^+)-N(t^-)=1\}}$ is an indicator function indicating a jump of a component, $N(t)$ is the number of jumps up to time t having a rate λ, and U_t is the

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intensity of the jump at time t.

We combine the two deterioration processes, continuous deterioration and occurrence of jumps, to find the overall deterioration of a single-component system as follows.

$$D_{sys,t} = D_t + J_t, \tag{4.6}$$

where $D_{sys,t}$ is the deterioration level of the system at time t.

4.2.2 A Multi-Component Deterioration Model

In this section, we generalize the single-component system deterioration model to construct a model for a multi-component system, where each component connects with other components and degrades randomly over time. Equation 4.6 in Section 4.2.1.1 now represents the deterioration level of one component.

Through an application of FMEA, systems are qualitatively analyzed for their failures characteristics and effects of the failures. With this analysis, we develop an understanding of how important a component is for the system's functionality and how a component is functionally related to other components. Components are defined as neighbors when they are known to be functionally connected to one another. Intensity of connection of component i has with component j is numerically defined by ρ_{ij}. If component A's functionality affects component B, then $\rho_{AB} > 0$. It should be noted that if component A affects component B, it is not necessary that component B affects component A to the exact same degree, i.e. $\rho_{AB} \neq \rho_{BA}$. ρ_{ij} can be estimated by several techniques, such as, FMEA, Analytical Hierarchy Process (AHP), using operational data estimation, vendors or experts' opinion. Further assumptions for the multi-component system deterioration model are as follows:

1. The system consists of N components.

2. Each component, i, has a deterioration process, with perfectly fit level of D_i^0 and maximum possible deterioration D_i^{max}, where i=1 to N.

3. A component fails if its deterioration exceeds its maximum deterioration level.

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4. The deterioration processes for each component are taken to be inherently independent of each other.

5. The deterioration level of a system is a function of the deterioration level of its components and the components' interaction with their neighbors.

6. The interaction coefficients between components are determined through an *a priori* FMEA analysis.

7. The system fails if its deterioration exceeds the maximum deterioration level, D_{sys}^{max}.

8. A decision maker has an option to maintain a system and/or its components if the deteriorations of the system and/or its components exceed the threshold level, D_j^{th} where $j \in \{1, \ldots, N, sys\}$.

9. The model incorporates the possibility that the system fails due to a part's failure.

Therefore, the deterioration of a system consisting of N components for each period t is given by,

$$D_{sys,t} = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} \rho_{ij} D_{i,t} D_{j,t}} + J_{sys,t}, \tag{4.7}$$

where $D_{i,t}$ is the deterioration level of component i. $J_{sys,t}$ represents the damage caused to a system due to failure of its component(s). Therefore, $J_{sys,t}$ helps us better mimic the system's behavior, where the system can be caused to fail when one of its parts fails.

We classify components into two types, critical components and non-critical components, where a critical component causes more damage to the system when it fails than a non-critical component. This classification is utilized in the definition of $J_{sys,t}$. We define $J_{sys,t}$ as follows.

$$J_{sys,t} = \sum_{i=1}^{N} F_{i,t} I_{\{D_{i,t} \geq D_i^{max}\}}, \tag{4.8}$$

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where $F_{i,t}$ represents the degree of damage of the system if component i fails at time t. $I_{\{D_{i,t} \geq D_i^{max}\}}$ is an indicator function indicating failure of component i. The validation of the multi-component model (Equation 4.7) is presented in Appendix A.

4.3 A Multi-Component Deterioration Model with Maintenance Actions

A failure or malfunction of the system results in disruption of production, reduction in quality of products' output, severe loss of lives and/or capital. Maintenance is performed to retain the system in a good functional state such that losses and unwanted incidents are minimized. In our analysis, maintenance is either a general repair activity or involves a complete replacement of component(s). Therefore, repair of a component means restoring it to a better state, while replacement implies restoring to its original state.

4.3.1 Repair or Replace Model

In Equation 4.7, the deterioration measure of the system is a bi-linear combination of its components' deterioration levels. As a result, reducing a component's deterioration level also decreases the deterioration measure for the system. In our analysis, we use a maintenance model to define the post-maintenance deterioration level of a component and apply it to obtain the new deterioration level of the system. A decision maker can choose between repair or replacement of component(s). After implementing a maintenance action at time t, the post-maintenance deterioration level of a component is calculated by Equation 4.9 for repair and Equation 4.10 for replacement.

$$D_{i,t^+} = (1 - u_i) D_{i,t^-}, \tag{4.9}$$

$$D_{i,t^+} = D_i^0, \tag{4.10}$$

where the repair factor (u_i) is modeled as a random variable with appropriate distribution based on data or vendor documentation.

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The cost of maintenance actions is affected by (1.) the type of maintenance action, such as, replace or repair, (2.) the criticality level of components, since the cost of a critical component is generally higher than that of a non-critical component, and (3.) the deterioration level of components, i.e., repairing a component with low deterioration is cheaper than repairing one with high deterioration, since the cost of preventive maintenance is always lower than the cost of corrective maintenance. As a result, the cost structure of maintenance actions is a function of three factors, the level of criticality of a component, the maintenance action chosen, and the deterioration level of the component(s), as shown in Table 4.1. Table 4.1 consists of four columns, where C_r and C_c are replacement and repair cost for a critical component, respectively, and C_n is a repair cost for a non-critical component. If considered necessary, further refinements in the cost structure can be incorporated. Since this is a strategic assessment, rather than a tactical, operational one, certain degree of coarseness in cost structural modeling is required and admissible.

Table 4.1: Cost Matrix

Action	Level of criticality	Deterioration level	Cost
Replace	Critical	Not relevant	C_r
	Non-critical		$0.8C_r$
Repair	Critical	$D_{i,t} < D_i^{th}$	$0.8C_c$
		$D_i^{th} \leq D_{i,t} < D_i^{max}$	$0.9C_c$
		$D_{i,t} \geq D_i^{max}$	C_c
	Non-critical	$D_{i,t} < D_i^{th}$	$0.8C_n$
		$D_i^{th} \leq D_{i,t} < D_i^{max}$	$0.9C_n$
		$D_{i,t} \geq D_i^{max}$	C_n

4.3.2 Enumerating the Maintenance Actions

We discuss triggers identifying a critical status of the system or its components and the corresponding maintenance actions in this section. A maintenance action is performed if the deterioration level of a component falls into a specified trigger zone or exceeds a certain deterioration level. In our paper, triggers are defined by the system's or component's deterioration level falling in the following zones.

1. System Failed Zone: $D_{sys,t} \geq D_{sys}^{max}$,

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2. System Warning Zone: $D^{th}_{sys} \leq D_{sys,t} < D^{max}_{sys}$,

3. Critical Component Failed Zone: $D_{i,t} \geq D^{max}_i$, where $i \in$ {Critical Component},

4. Non-Critical Component Failed Zone: $D_{i,t} \geq D^{max}_i$, where $i \in$ {Non-Critical Component},

5. Critical Component Warning Zone: $D^{th}_i \leq D_{i,t} < D^{max}_i$, where $i \in$ {Critical Component},

6. Non-Critical Component Warning Zone: $D^{th}_i \leq D_{i,t} < D^{max}_i$, where $i \in$ {Non-Critical Component},

The trigger zones are pre-specified by the provider so that the thresholds set for both the system and the component can detect suspicious condition before its breakdown. The threshold levels, D^{th}, should be identified such that they are an indication of a "prone to failure" stage, for instance, by using the search algorithm proposed in [42]. The trigger set can be made larger by distinguishing between different critical (or some non-critical) components for greater resolution in actions assigned to them. This, however, comes at a higher computational cost.

A list of candidate maintenance actions is an essential part of our search procedure for optimal maintenance strategy. After listing the maintenance actions, they are assigned to classes in order to make the search algorithm more efficient. We rank all the maintenance actions by their cost and aggressiveness in responding to the triggers from high to low. Thus, maintenance actions in a higher class are more aggressive and costly than maintenance actions in a lower class. For example, the maintenance actions in class 1 are more aggressive and costly than those in class 2. Each class can have more than one action when ties between them cannot be broken.

Table 4.2 presents a construction of a list of maintenance actions composed of eight factors. The first four factors (in the first 4 columns) are used to find a maintenance action for a primary part, while column 5-8 are factors used to find a maintenance action for a secondary part. A primary part is a part or a component

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whose deterioration level falls into a pre-specified trigger zones, while maintenance of a secondary part corresponds to an opportunistic maintenance performed on a component besides the primary component. A secondary part can be a neighbor of the primary part ($\rho_{ij} > 0$, where i is a primary part and j is a secondary part), which is indicated by "closest" in column 8 of Table 4.2, or any part, which is indicated by "All" in column 8 of Table 4.2. For example, if we consider the case: (1, Replace, Critical, $D_i^{th} \leq D_t^i < D_i^{max}$, Repair, Non-critical, N/R, and All) from columns 1 to 8 in Table 4.2, this corresponds to "Replace a Critical Component whose Deterioration is between D_i^{th} and D_i^{max} and Repair Every Non-Critical component Regardless of its Deterioration." Note that "N/R" is an abbreviate for "Not Relevant", and "N/A" is an abbreviate for "Not Applicable".

Table 4.2: List of maintenance actions

Primary part(s)				Neighbor of primary part(s)			
Primary parts	Action	Level of criticality	Deterioration level	Action	Level of criticality	Deterioration level	Location
All	Replace	N/R	N/R	N/A	N/A	N/R	N/A
1	Repair	Critical	$D_{i,t} < D_i^{th}$	Replace	N/R	$D_{i,t} < D_i^{th}$	All
	Do nothing	Non-critical	$D_i^{th} \leq D_{i,t} < D_i^{max}$	Repair	Critical	$D_i^{th} \leq D_{i,t} < D_i^{max}$	Closest
			$D_{i,t} \geq D_i^{max}$	Do nothing	Non-critical	$D_{i,t} \geq D_i^{max}$	

We create over 140 actions from Table 4.2 and divide them into 47 classes using their maintenance cost and aggressiveness in response to a trigger. The number of maintenance actions in a class varies from one to three. To optimize the choice of maintenance actions, we need to match one of the 140 actions for all the 6 triggers. Dividing maintenance actions into classes helps us search for the optimal solution more efficiently, as discussed in the next section.

4.4 Simulation Based Optimization Problem

This section discusses the simulation method for the deterioration model developed in the earlier sections and presents a search algorithm to find the optimal choice of maintenance actions for the trigger events.

Generally, the deterioration measure of a component can be obtained analytically by solving its stochastic differential equation representation. However, in our case a non-decreasing function transformation of the two-stage model and impos-

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ing controls over the process due to choice of maintenance actions results in sizable complexity. Thus, obtaining analytical solutions is difficult. As a result, we choose to obtain solutions numerically by using continuous simulation techniques. Among the various numerical simulation techniques available for the continuous deterioration model for the components, we use the Euler scheme [205], since this scheme is simple, yet provides reasonable accuracy.

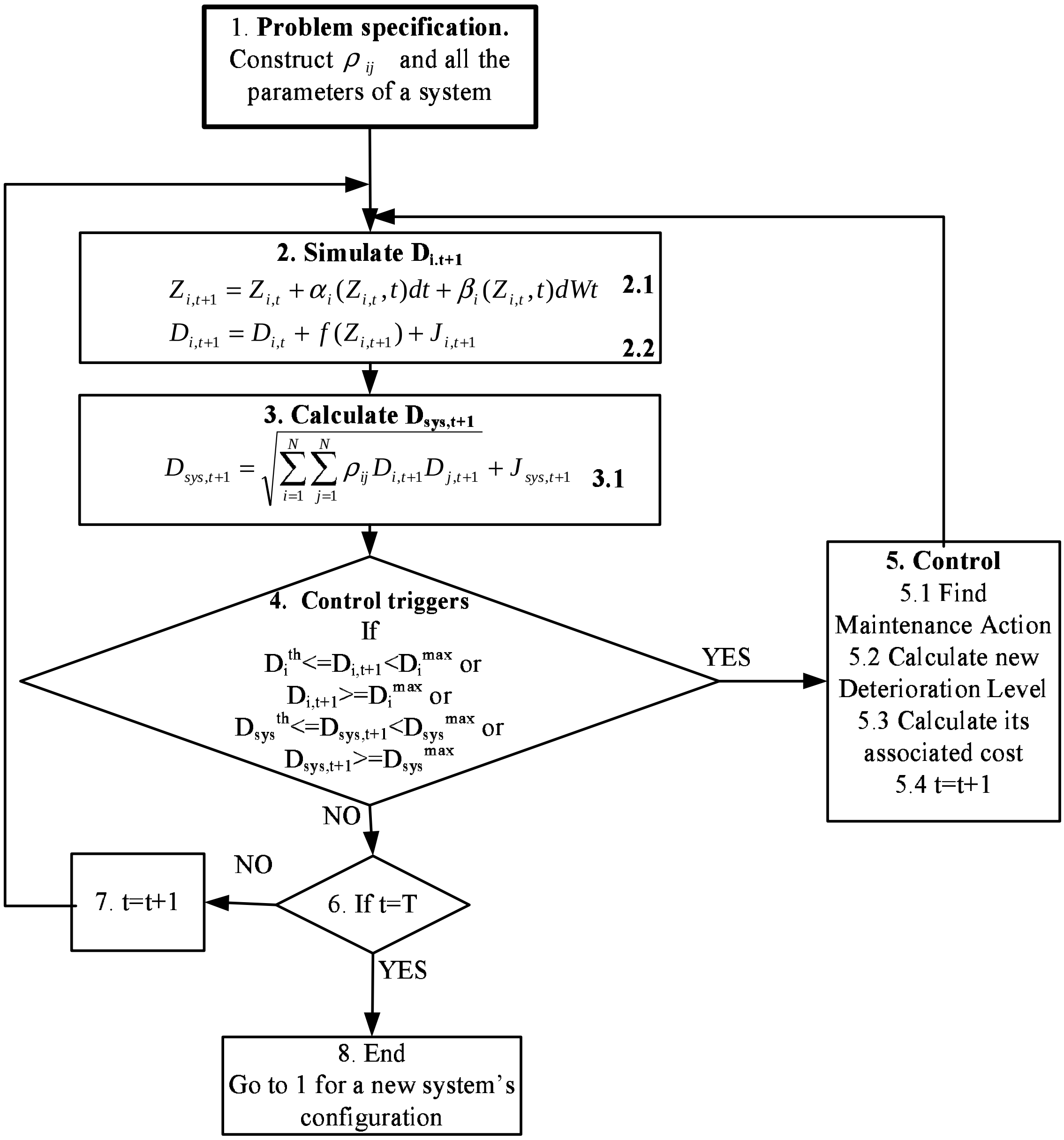

Figure 4.1: Flow chart of a simulation of a deterioration process of a system

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Figure 4.1 presents a flow chart of the algorithm for simulation of the deterioration process and its interactions with maintenance actions. First, we develop the problem specification, where we estimate $\alpha_i(Z_{i,t},t); \beta_i(Z_{i,t},t); \rho_{ij}$; the arrival rates for the jump process, λ_i, and its intensity U_i; parameters for repair and replacement, u_i, and corresponding costs, c_c, c_r and c_n. After a complete specification of the problem, we begin the simulation process to find the deterioration measure of each component i in box 2 of Figure 4.1. Given the deterioration level at time t, the process advances based on discretization of Equation 2.1 in Figure 4.1, where we find the deterioration level of a component at time $t+1$. First, we generate a ΔW_t, realization of increments in the Wiener process in time step [t,t+1], where one time step is equal to one day in our model. We can find $Z_{i,t+1}$ from Equation 2.1 in Figure 4.1. Once we get $Z_{i,t+1}$, we transform it by using an exponential function (the second term in Equation 2.2, Figure 4.1) to ensure a positive value, which is an increment in the deterioration of a component due to the continuous part.

For sudden changes in deterioration, first we find when a jump occurs by generating arrivals for the jump process. If there is a jump at time t, we generate its intensity using its underlying distribution. If there is no jump, the jump deterioration term will be zero. After we find $J_{i,t+1}$, we can find the deterioration level of a component i by using Equation 2.2 in Figure 4.1.

Once we find the deterioration level of all the components, we obtain the deterioration of the system by Equation 3 in box 3 of Figure 4.1. The $J_{sys,t+1}$ in this equation can be found by checking whether there is a failed part. If there is a failed part, we generate the $J_{sys,t+1}$ from its underlying distribution discussed in Equation 4.8.

If the deterioration of a component or of the system falls in a trigger zone (box 4 in Figure 4.1), a maintenance action generated by the maintenance-action generator is performed, and the after-maintenance deterioration levels are determined using the repair or replacement model discussed in Section 4.3.1 (box 5 in Figure 4.1). The process repeats until reaching the planning horizon, T.

For the optimization part, our objective function is to minimize the expected long run cost of maintenance and failures. Each maintenance action, A_k, has its

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associated cost ($C(A_k)$) which is constructed by using Table 4.1. The failure cost (C_F) is a function of the deterioration of a component and the system. It is estimated from several costs, such as, safety cost, an opportunity cost for response time, and a penalty cost of not meeting customer satisfaction. In our model we take the failure cost of a critical or a non-critical component to be equal to the replacement cost of that component, while the failure cost of the system is double the replacement cost of the most costly critical component. Other appropriate constructions of a model for failure costs can be accommodated. The total cost (TC) is as follows:

$$TC = \int_0^T C(A_k, t) + C_F(D_{i,t} I_{\{D_{i,t} \geq D_i^{max}\}}, D_{sys,t} I_{\{D_{sys,t} \geq D_{sys}^{max}\}})dt, \qquad (4.11)$$

where $C(A_k, t)$ is a cost of maintenance action at time t.

4.4.1 Optimal Search Algorithm

We present our search algorithm in this section. The search algorithm tries to span the entire solution space after an initial class is assigned to each trigger. It attempts to jump to another class if the objective function is improved by the jump. The search for actions for each trigger stops if the objective function does not improve or no further jumps are possible for that particular trigger.

Our search algorithm has three main procedures. The first procedure is initialization, where we assign a maintenance class to each trigger. We assign more aggressive maintenance classes to the more severe triggers, for example, a maintenance class assigned to the system warning zone is less aggressive than a maintenance class assigned to the system fail zone. The second procedure determines the search direction, where we identify a direction for each trigger that improves the objective function value. The third procedure searches for a maintenance action from the new class in the direction identified by the second procedure. Procedures 2 and 3 are repeated until the objective function stops improving or no further jumps between classes are possible. Before describing the search algorithm, we need to define the following terms.

T_i: i^{th} trigger event, $1 \leq i \leq 6$,

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A_{T_i}: maintenance action corresponding to the i^{th} trigger event,

A: a set of maintenance actions, $A = \{A_{T_i}\}$,

C_{T_i}: maintenance class for A_{T_i},

K_{T_i}: search direction adopted while at C_{T_i}.

m: control to reverse the search direction; $m \in \{0, 1\}$.

k: iteration count updated when a maintenance action for a trigger is changed.

n: number of times actions for the entire trigger set are evaluated.

1. **Initialization**

    Set n=0, m=0, k=0, A^{-1} = most aggressive action set.

    Assign a class C_{T_i} for each trigger T_i.

    Exhaustively search all maintenance actions in every C_{T_i}
    to obtain the initial solution ($A^0_{T_i}$).

    Set $K_{T_i} = 1$. We choose to span our search to a weaker maintenance class first
    because a weaker class has a lower maintenance cost.

Optimal Search

Do while $A^{n-1} \neq A^n$

Set n=n+1.

For $i = 1$ to 6

2. **Determining the search direction**

    If m = 0, Set $K_{T_i} = K_{T_i}$; Else, Set $K_{T_i} = -K_{T_i}$; End if.

    Fix maintenance actions corresponding to T_j; $j \neq i$, i.e.,
    set $A^n_{T_j} = A^{n-1}_{T_j}$ if $j \neq i$.

    Set $C_{T_i} = C_{T_i} + K_{T_i}$.

3. **Search maintenance action**

    Search maintenance actions in class C_{T_i} to obtain the solution, $A^n_{T_i}$.

    If the total cost is improved then

    Update the total cost and the solution and set m=0.

    Set k=k+1.

    if ($C_{T_i} = 1$ or $C_{T_i} = 47$), set $K_{T_i} = 0$ End if.

    Else (if the total cost is not improved and m = 0) then

    Set m=1 and go to 2.

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Else (if the total cost is not improved and m = 1) then

Set $C^*_{T_i} = C_{T_i} - K_{T_i}$, $K_{T_i} = 1$, $m = 0$.

End if

End For

End Do While

4. Return the optimal solution.

After obtaining the optimal solution, a decision maker should perform a detailed sensitivity analysis of the optimal solution. This is essential specifically with respect to the most critical abstractions in the model, for example, defining component groups to assign triggers, trigger levels, and corresponding common actions. The sensitivity analysis helps assess the optimal solution and determine the necessary refinements.

4.5 Numerical Example

In this section, results are presented to demonstrate the development of the model and implementation of the simulation and search algorithm. We set up a simple serial system consisting of five components. For simplicity, we assume that the drift and the diffusion terms, α and β, are constant. The corresponding interaction set up is given in Table 4.3.

Table 4.3: The interaction coefficients used in the illustrated problem

ρ_{ij}	1	2	3	4	5
1	1	0.5	0	0	0
2	0	1	0.5	0	0
3	0	0	1	0.5	0
4	0	0	0	1	0.5
5	0	0	0	0	1

Table 4.4: The parameter used in the illustrated problem

	Initial Value	Drift term α	Diffusion term β	Jump arrival rate λ	Threshold Value	Maximum Value	Critical	Jump Intensity (U_i)
Comp 1	U(0,40)	2	5	1	55	60	X	$\lvert N(5000, 1000)\rvert$
Comp 2	U(0,40)	0.1	2.5	2	55	60		$\lvert N(5000, 1000)\rvert$
Comp 3	U(0,40)	0.5	3	2	55	60	X	$\lvert N(5000, 1000)\rvert$
Comp 4	U(0,40)	0.5	2.5	2	55	60		$\lvert N(5000, 1000)\rvert$
Comp 5	U(0,40)	1	2	0	55	60		$\lvert N(5000, 1000)\rvert$
System					128	140		

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The parameters for each component deterioration evolution model, threshold and criticality are shown in Table 4.4. Components 1 and 3 are critical components, while Components 2, 4 and 5 are non-critical. The relationship between a failed component and the deterioration of the system is presented in Table 4.5. Maintenance costs and the recovery values are presented in Table 4.6.

Table 4.5: A relationship between a failed component i and magnitude of deterioration $(F_{i,t})$ of the system

Component	$F_{i,t}$	Probability
Non-critical component	10	0.25
	15	0.50
	25	0.25
Critical component	20	0.25
	25	0.50
	35	0.25

Table 4.6: Maintenance costs and recovery values

Action	Level of criticality	Deterioration level	Cost per component	Recovery value	R
Replace	Critical	Not relevant	500	$D_{i,t^+} = 0$	Not applicable
	Non-critical		400		
Repair	Critical	$D_{i,t} < D_i^{th}$	320	$D_{i,t^+} = R \times D_{i,t^-}$	$R \sim U(0, 0.3)$
		$D_i^{th} \leq D_{i,t} < D_i^{max}$	360		$R \sim U(0, 0.4)$
		$D_{i,t} \geq D_i^{max}$	400		$R \sim U(0, 0.5)$
	Non-critical	$D_{i,t} < D_i^{th}$	240		$R \sim U(0, 0.3)$
		$D_i^{th} \leq D_{i,t} < D_i^{max}$	270		$R \sim U(0, 0.4)$
		$D_{i,t} \geq D_i^{max}$	300		$R \sim U(0, 0.5)$

We begin our search procedure by assigning class 1, 2, 11, 13, 27 and 46 to trigger 1 to 6, respectively, as shown in Table 4.7. Initial classes are selected so that more aggressive maintenance class is assigned to more severe trigger, and the initial solution is obtained quickly. Moreover, we have selected the initial classes such that several of our initial choice of classes have only one maintenance action in them. After assigning the initial maintenance class to each trigger, we perform an initial search to find the initial solution for the problem. We use 300 replications to evaluate the objective function. The total expected cost and the corresponding confidence intervals are seen to stabilize in our simulation experiments with 300 or more replications. The search algorithm converges after 34 iterations yielding the optimal solution (OPT) as shown in Table 4.7. The optimal solution results in a

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25% cost reduction from the initial solution.

Table 4.7: The table shows an initial solution and the optimal solution (OPT) of the problem

Trigger	Initial solution		Optimal solution	
	Class	Action Description	Class	Action Description
1 System Fail	1	Replace every component	2	Replace every critical component Replace every non-critical component whose deterioration exceeds threshold
2 System Warning	2	Replace every critical component Replace every non-critical component whose deterioration exceeds threshold	3	Replace every critical component Replace every non-critical component whose deterioration exceeds maximum
3 Critical Comp. Fail	11	Replace every critical component	11	Replace every critical component
4 Non-critical Comp. Fail	13	Repair every component	13	Repair every component
5 Critical Comp. Warning	27	Replace a component whose deterioration exceeds threshold Repair its neighbor	24	Replace a critical component whose deterioration exceeds threshold Replace its neighbor whose deterioration exceeds threshold
6 Non-critical Comp. Warning	46	Repair a non-critical whose deterioration exceeds threshold.	45	Repair a non-critical component Repair its neighbor whose deterioration exceeds threshold
Total cost	33485		24942	
Performance Analysis				
System Warning	0.8		0.7	
Comp. Fail	16		15	

4.5.1 Analysis of the Optimal Solution

For analyzing the performance of our search algorithm, besides the objective value, we define the following measures for comparing solutions: the average number of times the system gets into the warning zone, and the average number of times components fall in their failed zones over the entire planning period. The optimal solution is compared against three other solutions, the initial solution and two carefully selected alternative solutions. One alternative solution is a risk-averse solution, where a decision maker selects very aggressive actions to yield the minimum number of failures (both for the components and the system) over the planning period, and the another is a risk seeking solution, where a decision maker selects non-aggressive actions to yield low maintenance cost each time maintenance is performed. Comparative performance of the optimal solution is presented in Tables 4.7 and 4.8.

The risk seeking solution attempts to lower cost by picking a less aggressive and low cost maintenance action for each trigger. As seen from Table 4.8, however, the risk seeking solution lands up performing worse than other solutions in terms

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of all the performance measures. The average number of times the system falls in the warning zone and the average number of components failed are much more than those for the optimal solution. As a result, while the maintenance cost of each action is low, the expected long run cost due to failures is much worse. For the optimal solution (OPT), the average number of times the system falls in the warning zone is 0.7 in a 10 year planning period, and the average number of times a component fails is 15. The system itself is never observed to fail in the 10 year period. This performance is better than the initial solution. Moreover the optimal solution is more cost efficient than the initial solution causing a 25% cost reduction. In case of the risk averse solution, the average number of times the system falls in the warning zone is further reduced, and so has the average number of failed components, as a result of very aggressive maintenance actions. This comes at a 17% increase in costs from the optimal solution.

4.5.2 Assuring Robustness of the Optimal Solution

In this section, sensitivity analysis of the optimal solution is discussed. In general, the parameters of the system, such as, the drift coefficient (α_i), the diffusion

Table 4.8: The performance analysis of the optimal solution compares with other two solutions

Trigger	Risk seeking solution		Risk averse solution	
	Class	Action Description	Class	Action Description
1 System Fail	4	Replace every critical component whose deterioration exceeds its threshold Replace every non-critical component	1	Replace every component
2 System Warning	7	Replace every critical component whose deterioration exceeds its threshold Repair every non-critical component	2	Replace every critical component Replace every non-critical component whose deterioration exceeds threshold
3 Critical Comp. Fail	14	Repair every critical component whose deterioration exceeds its threshold	8	Replace every non-critical component whose deterioration exceeds its max Repair every critical component
4 Non-critical Comp. Fail	27	Replace a component whose deterioration exceeds its threshold Repair its neighbor	13	Repair every component,
5 Critical Comp. Warning	27	Replace a component whose deterioration exceeds threshold Repair its neighbor	27	Replace a component whose deterioration exceeds threshold Repairs its neighbor
6 Non-critical Comp. Warning	46	Repair a non-critical component whose deterioration exceeds threshold	38	Repair every non-critical whose deterioration exceeds threshold
Total cost	37800		29345	
Performance Analysis				
System Warning	1.7		0.25	
Comp. Fail	23		10	

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coefficient (β_i), and parameters for the jump process, are estimated using reliability data of the system and its components, and the maximum deterioration levels of a component and the system are often determinable to a certain accuracy from design specifications and expert opinion. The decision maker has more discretion to choose the threshold level for the components (D_i^{th}) and the system (D_{sys}^{th}) that define the warning zones. Thus, we focus on sensitivity analysis with respect to changes in the threshold levels for the deterioration of the components and the system.

Table 4.9 presents the range of the threshold values for which OPT stays optimum and changes in optimal actions beyond these threshold ranges. Components are ranked from the widest range to the narrowest. The non-critical components have wider range than the critical components. Drift and diffusion coefficients of a component play a significant role in this sensitivity analysis, specifically for critical components. For instance, a high coefficient of component 1 results in component 1 threshold being the most sensitive one.

Table 4.9: Range of the threshold values for which the optimal solution (OPT) stays optimal and the modifications when the threshold values are beyond the range

	Threshold	Changes at the lower bound	Changes at the upper bound
Comp. 5	50-58	Trigger 6 changes to "Repair every non-critical component" $TC^* = 21953$	Trigger 6 changes to "Repair a non-critical component" $TC^* = 23909$
Comp. 2	51-58	Trigger 6 changes to "Repair every non-critical component" $TC^* = 27741$	Trigger 6 changes to "Repair a non-critical component" $TC^* = 25413$
Comp. 4	51-57	Trigger 6 changes to "Repair every non-critical component" $TC^* = 25138$	Trigger 6 changes to "Repair a non-critical component" $TC^* = 26896$
Comp. 3	52-57	Trigger 5 changes to "Replace a component whose deterioration exceeds threshold and repair its neighbor" $TC^* = 30742$	Trigger 5 changes to "Replace a critical component whose deterioration exceeds threshold" $TC^* = 24357$
Comp. 1	52-56	Trigger 5 changes to "Replace a component whose deterioration exceeds threshold and repair its neighbor" $TC^* = 28841$	Trigger 5 changes to "Replace a critical component whose deterioration exceeds threshold" $TC^* = 24409$
System	124-136	Trigger 2 changes to "Replace every component" $TC^* = 26048$	Trigger 2 changes to "Replace every critical component whose deterioration exceeds threshold Replace every non-critical component whose deterioration level exceeds threshold" Trigger 5 changes to "Replace a components whose deterioration exceeds threshold and its neighbors" Trigger 6 changes to "Replace a non-critical component and repair its neighbor" component" $TC^* = 28572$

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In the sensitivity analysis, the threshold level is changed for a component; however, actions are still determined for the component group, i.e., all critical or non-critical components as a group. Therefore, the optimal action choice is an outcome of how the change in threshold impacts the entire group of components for which an optimal action is being sought. As the threshold level for any of the components is gradually lowered, thus increasing the width of its warning zone, after a point the optimal action changes to one that is more aggressive. Lowering of the threshold results in visiting the warning zone more often; a more aggressive action attempts to lower the frequency of these visitations.

When a threshold for a component is gradually increased, its warning zone is narrowed, a reverse effect on the optimal solution is observed. The optimal action becomes less aggressive, even though the warning zone and the failure zone are visited almost equally often. This is explained from the fact that since the threshold is higher the decision maker feels that he can get away with less costly and less aggressive action to maintain staying away from the warning zone. Note that the objective value for the OPT solution (with the original threshold) is lower than most of the objective function values for new optimal solutions reported in Table 4.9. This indicates that our careful choice of original component thresholds is good.

A similar explanation applies to the system level, when the gap between the threshold and the maximum level of the system is wide. However when the threshold level of the system is close to the maximum level, we perform more aggressive actions for the components reaching their warning zone, while the action for the system reaching its warning zone is weakened. The consequence of aggressive action for the components is that the system rarely reaches its warning zone as the cost of system's failure is high. Therefore, the risk of the system's failure is hedged by responding more aggressively to components reaching their warning zones.

Figure 4.2 presents the change in objective function value due to change in the system threshold level in the range $124 - 136$. Note that for this range of system threshold, OPT stays optimum. The maximum possible deterioration of the system is set at 140. The objective function is found to be the smallest when the system threshold is set at 133. The threshold and the maximum for deterioration of the

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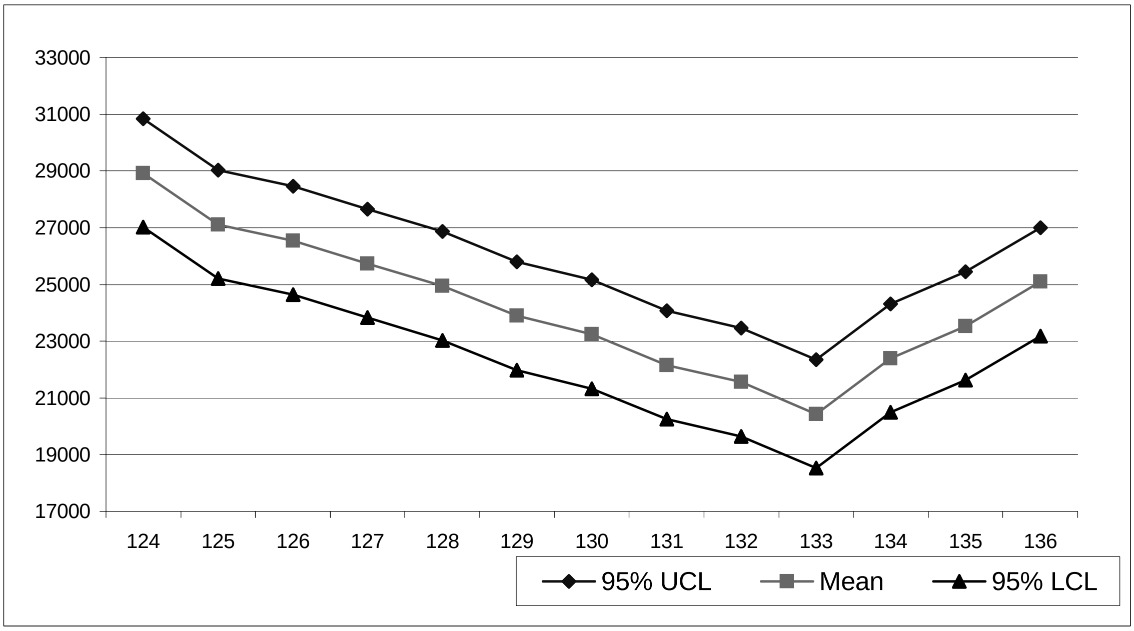

Figure 4.2: The confidence interval of the expected total cost of *OPT* when the range of threshold values of the system is between 124 and 136

components are fixed at 55 and 60, respectively.

As we can see from Figure 4.2, the expected long run cost is higher when the threshold level for system deterioration is low, since the system reaching its warning zone results in more frequent maintenance actions. However, when the threshold level for system deterioration is increased to 133, the expected long run cost starts to increase. The threshold value is now too close to the maximum deterioration level, thus the system tends to succumb to failure without passing through the warning zone resulting in large failure costs.

Following the systems' case, Figure 4.3 is a similar plot of objective function values for varying component thresholds. Here again the wide warning zone results in excessive maintenance, while a narrow warning zone results in the incapability of detecting a "prone to failure" stage, resulting in frequent failures. However, the effect of critical and non-critical components is different. Specifically, one unit change in the threshold value of a critical component has more effect on the expected long run cost than that of a non-critical component, since the maintenance cost and impact of deterioration of a critical component is higher than that of a non-critical component. Moreover we consider opportunistic maintenance when a critical or a

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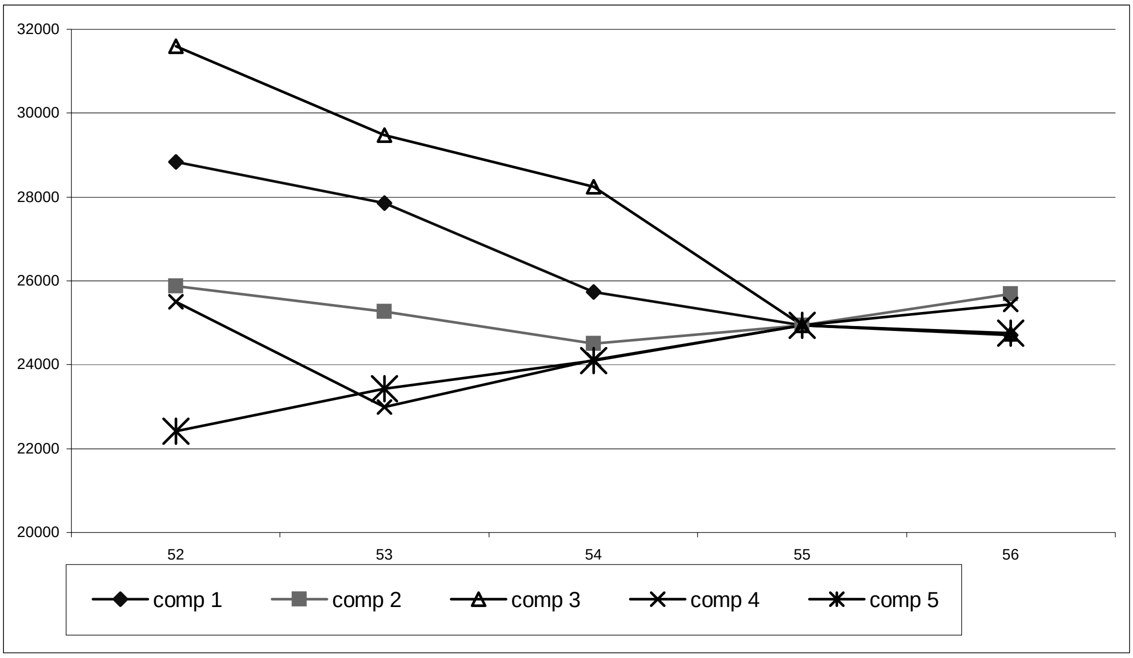

Figure 4.3: The expected total cost of OPT when the ranges of threshold values of components are between 52 and 56

non-critical component is in the warning zone. Among the critical components, the ones that are more intensely connected with other components are more sensitive to changing thresholds. Between critical components 1 and 3, it is clear from Figure 4.3 that the expected long run cost displays larger changes in magnitude when the threshold is changed for component 3 than for component 1. This is because the maintenance action for component 3 involves more neighbors than component 1.

4.6 Conclusions

This chapter has developed a framework to determine strategically optimal maintenance actions for a multi-component system, where each component of the system degrades continuously with jumps. The status and criticality of the components determine the overall health of the system. Different maintenance actions in response to system condition help improving the status of the system. The model is solved using an Euler-scheme based continuous simulation to find the deterioration level of the components and the system. Strategically optimal maintenance actions that minimize a combination of maintenance and failure costs are found for the

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system and its components using a search procedure.

The framework is applied to a sample configuration of a multi-component system. The optimal solution found recommends making opportunistic maintenance corresponding to most triggers, except when a non-critical component falls in the warning zone. The optimal maintenance strategy is both cost-effective and performs well in terms of number of times the system falls in the warning zone or average number of component failures. A detailed sensitivity analysis is also performed for the thresholds that define the warning zones for the system and its components.

This chapter achieved the analysis of the optimal maintenance actions for a single system, where we focused only on product risks. The analysis in this chapter assumed that there is no risk during the service delivery process. However, the service delivery process is not deterministic. The provider is also exposed to risks that occur during the service process. As a result, service risks are a very important issue for the provider. The challenge is to efficiently manage the service delivery of LTSAs so that the risks are minimized, while fulfilling the service's requirements. This problem is developed in the next chapters.

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CHAPTER 5
Developing Optimal Service Delivery of Long-Term Service Agreements Under Service Risks

The previous chapters identified the sources of risks of the service delivery of LTSAs and found the maintenance strategy when we focused only on product risks. In this chapter, we develop a quantitative risk assessment and management framework for designing an optimal service operations strategy for the delivery of LTSAs. Since the provider can be exposed to the possibility of extensive losses and can endanger product's end-consumers, a rigorous risk assessment and management framework helps the provider better design its service delivery strategy in order to prevent catastrophic losses. The framework helps the provider thoroughly analyze risk exposures and the impacts of the service delivery, and allows the provider to take advantage of different kinds of risks, and to better manage the risks more effectively.

5.1 Introduction

While we have analyzed maintenance strategy which minimizes long-term maintenance costs of the service delivery of LTSAs from a product risk perspective in Chapter 4, this chapter focuses on developing service operations strategy when both product risks and service risks are incorporated. We refer the reader to Chapter 3 for an extensive review of risks of LTSAs. In that chapter, we dissected the risks of the service delivery in order to help the provider understand different kinds of risks and develop an efficacious risk management strategy.

In this chapter, a quantitative framework for risk analysis and management of the service delivery of LTSAs from the provider's perspective is developed, since the provider plays the most central role in defining and delivering the service. The framework focuses on the service part of the service delivery, where it includes several important sources of risks, such as, engineering reliability, maintenance, service infrastructure, contract definitions, and the financial structure of the service.

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In particular, the framework concentrates on the analysis of the strategic risks of a single LTSA. The provider must thoroughly understand risks that occur in the service process of a single LTSA before a risk management and service strategy for a portfolio of LTSAs is developed. Without thoroughly understanding the risk profile of one contract, the provider cannot fully take advantage of the interrelations between different kinds of risks and manage the risks of a portfolio effectively. A portfolio analysis is also important, since a provider sells many LTSAs to take advantage of economics of scale. The framework in this chapter facilitates an in-depth analysis of service design for a single LTSA, and can be instantiated for a specific type and model of product after appropriately adapting the models to the context.

The problem of developing the service delivery of LTSAs bears several similarities with many problems addressed in the literature discussed in Chapter 2, i.e., maintenance management, inventory management, service operations management, and financial and risk management. The maintenance management problem and the inventory management problem share a similar view where they try to optimize the operational costs. While the maintenance management problem finds an optimal maintenance strategy that minimizes maintenance and failure costs [248, 161], the inventory management problem finds an optimal inventory strategy that minimizes inventory costs and reduces backorders [82, 220, 68]. The service operations management problem aims to develop a service process which maximizes a customer's experience or the quality of a service process [348, 349, 354]. The financial and risk management problem deals with developing effective risk mitigation plans that maximize a firm's value [8, 203, 140, 303, 261, 275]. These problems are often addressed separately in the literature, even though an integrated analysis of these problems can lead to a higher firm's value [87, 316].

The problem of developing service delivery of LTSAs deals with designing end-to-end service operations for sustaining the functionality of a product for customers. Therefore, it combines several features of maintenance management, inventory management, service operations management, and financial and risk management problems. The provider needs to develop maintenance schedule to ensure

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the long-term functionality of the product through an assistance of a supporting service infrastructure that the provider puts in place. During maintenance period, components may be removed from the product. Hence, the provider would want to maintain and manage its inventory that minimizes inventory costs and reduces back-orders. Moreover, the provider has to design an efficient service operations process and a facilitating service infrastructure in order to fulfill the customer's requirements with lowest costs and risks and to create proper risk management plans conforming to the provider's business strategy. Our challenge is to develop an integrated risk management framework which takes into account these features in order to find an optimal service operations strategy for the delivery of LTSAs.

Organization of the rest of the chapter is as follows. We outline the development of the framework of the risk assessment and management in Section 5.2. This is followed by a detailed discussion of the framework in Section 5.3. Section 5.4 describes a simulation method employed to find risks of a service delivery strategy. The analysis is then enhanced to solve for a service strategy that minimizes risks in Section 5.5, followed by the conclusions in Section 5.6.

5.2 Overview of A Risk Assessment and Management Framework

This section gives an overview of the risk assessment and management framework to motivate the development of models that facilitate the service delivery. The dissertation focuses on the service part of the delivery of LTSAs, where we focus on post installation risks which include risks of contract setup and specification, risks of service infrastructure, and risks of financial resource management. Figure 5.1 outlines important sources of risks that are incorporated in the framework. As shown in Figure 5.1, risks of product (engineering) reliability, risk of maintenance, and risks of contract definitions affect risks of contract setup and specifications as discussed in Chapter 3. To develop the framework, a bottom-up approach is employed where the provider needs to fully understand risks of product (engineering) reliability (box 1 in Figure 5.1) before it can progress to consider risks of maintenance (box 2 in Figure 5.1) and so on, until the top level of financial analysis is reached in box 5 of

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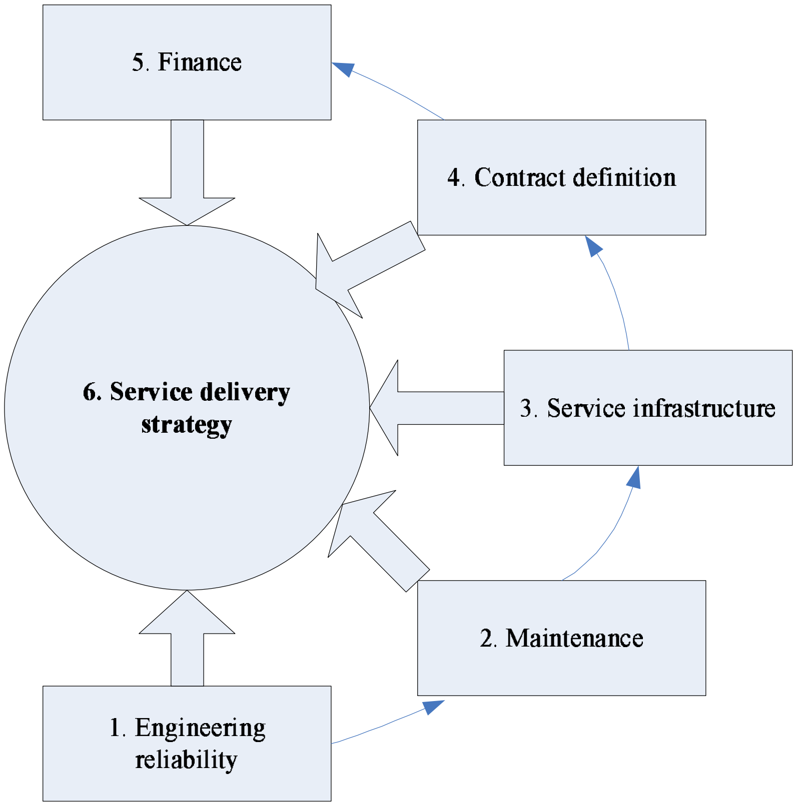

Figure 5.1: An overview of models development in the framework

Figure 5.1.

Our challenge is to develop a framework that assesses these five aspects of risks which are potentially complex and interrelated. The analysis begins with the risks of engineering reliability of the product, since the product is fundamental to the service delivery. The objective of the engineering reliability model is to infer the condition or the health of the product from information obtained from the sensor systems embedded in the product. Empowered by this information and the sensor technology, the provider utilizes a condition based maintenance (CBM) strategy for its products. CBM helps the provider make better maintenance decisions. It is estimated that CBM can reduce maintenance costs by around 50-80% [310].

For a successful service delivery, the provider needs to carefully plan and efficiently manage its service infrastructure. The service infrastructure is defined as physical components and knowledge-based components facilitating the service delivery. The physical components include a monitoring system, spare part, repair

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facilities, human resources, etc. The knowledge-based infrastructure includes the information systems and information technology supporting the service delivery. The service infrastructure affects not just a single contract but all the contracts sold by the provider, since all contracts share the same service infrastructure. The challenge for the provider is to use and manage every component in the service infrastructure so that the provider can meet the service's requirements with minimal costs and risks.

An LTSA is a contract between the provider and the customer. In a contract, the provider guarantees a certain level of output obtainable from the product to the customer during a contract period in exchange for a fee. The customer agrees to operate the product under specified conditions and to give the provider access to maintain the product. Penalty fee structures are agreed upon if the contract is breached. For example, the provider may have to pay a penalty fee to its customer if it cannot deliver the service as specified in the contract. The provider evaluates its financial risks from the costs incurred in boxes 2-4 of Figure 5.1 and revenues received from the customer. The provider can control its risk profile by improving the design of the product and its service delivery, carefully creating contract specifications, designing appropriate revenue and penalty fee structures, and eventually creating a portfolio of LTSAs by considering hedging and/or diversification strategies for the portfolio [120, 121, 162, 217, 330].

5.3 Building the Framework

This section presents the scope of the analysis and the development of the framework in detail by constructing models that are pertinent to our analysis. Figure 5.2 presents the layout for the construction of the framework. The framework begins with the construction of the engineering reliability property where we create a model to evaluate the condition or the health of the product (box 1 of Figure 5.2). Employing CBM, the provider makes maintenance decisions based on the condition of the product. In box 2 of Figure 5.2 models pertinent to maintenance are developed. In particular, models capturing the effects of maintenance actions, maintenance cost and downtime are created. This is followed by the analysis of

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the service infrastructure. The service infrastructure models capture the behavior of a monitoring system and the evolution of inventory levels. Contract definitions in box 4 of Figure 5.2 formulate the quantification capturing the performance of a contract and its penalty fee structure. Finally at the top level (box 5 in Figure 5.2), we create a revenue model and assess the profits and risks of the service delivery for the provider.

5.3.1 Engineering Reliability

The construction of the framework begins at the lowest level (box 1 in Figure 5.2) where a model representing engineering reliability of the product is constructed. The objective of this section is to find an evolution of the condition of the product (system) over time. The condition or the health of the product (measured deterioration) is constructed in terms of information that is obtained from sensors-based monitoring systems and is pertinent to the functionality of the product, e.g., temperature, pressure, vibration, and crack length. This chapter assumes that the information obtained from the sensors can be transformed to a deterioration measure of a system after appropriate transformations, [151, 152]. This section begins by reviewing continuous-time jump deteriorations model which is used to infer the condition of a product proposed in Chapter 4.

5.3.1.1 A Continuous Deterioration Model with Jumps

This section summarizes the model presented in Chapter 4, where the product consists of several components whose deterioration levels directly affect and summarize the deterioration of the product. The deterioration of components and the product consists of two important parts, i.e., a continuous deterioration and a jump (sudden change) in deterioration.

Consider a component that degrades randomly and continuously over time. The degradation of the component lies between C_i^0 and C_i^{max}, where C_i^0 is the perfectly fit deterioration level of the component, while C_i^{max} is the maximum deterioration allowed for the component. The component definitively fails if its deterioration level exceeds C_i^{max}. The goal is to find the evolution of the deterioration process. The increment of the deterioration is modeled by,

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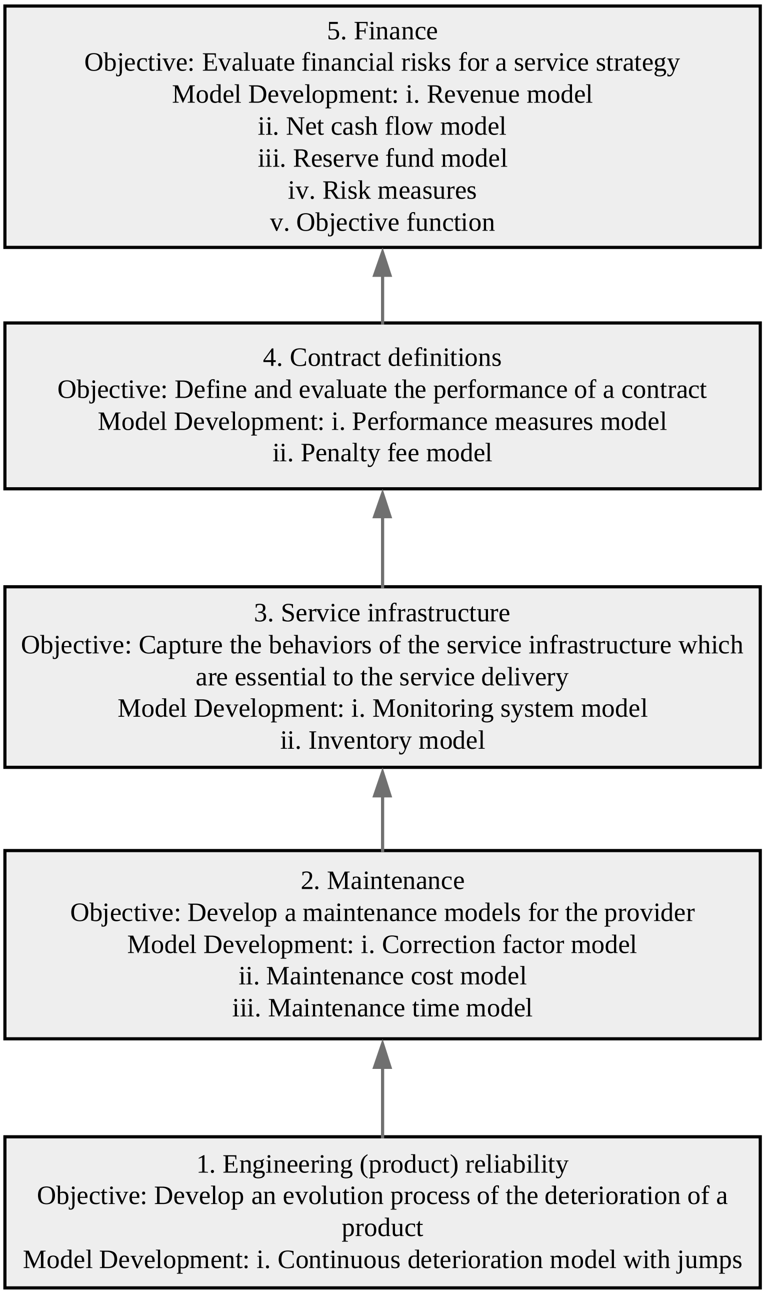

Figure 5.2: A flow of model developments of risk assessment

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$$\Delta C_{i,t} = \alpha(C_{i,t}, t)\Delta t + \beta(C_{i,t}, t)\Delta\chi_{i,t}, \tag{5.1}$$

where $\Delta C_{i,t}$ is the increment in deterioration in time (Δt), and $\Delta\chi_{i,t}$ is the increment of an appropriately chosen stochastic process. $\alpha(C_{i,t}, t)$ is the deterministic rate of increase in deterioration level, termed as the drift coefficient, and $\beta(C_{i,t}, t)$ is the variability coefficient, termed as the diffusion coefficient. Specific forms for these functions, $\alpha(C_{i,t}, t)$ and $\beta(C_{i,t}, t)$, will need to be chosen based on the reliability of each component. The parameters in these coefficients will in general be estimated from observations of a system's deterioration process, or from the engineering design analysis or reliability tests data. $\chi_{i,t}$ can be chosen to be a Wiener process, Ornstein-Uhlenbeck process, Poisson process, etc, [112].

For some choices of $\chi_{i,t}$ process, such as a Weiner process, by Equation 5.1, it is possible that the deterioration decreases with time because $\Delta C_{i,t}$ can be negative. Thus, we modify Equation 5.1 so that the deterioration of components is a non-decreasing function of time as follows:

$$\Delta X_{i,t} = \alpha(X_{i,t-1}, t)\Delta t + \beta(X_{i,t-1}, t)\Delta W_{i,t}, \tag{5.2}$$

$$\Delta C_{i,t} = f(X_{i,t})\Delta t, \tag{5.3}$$

where $X_{i,t}$ is an Ito process, and W_t is the Weiner process. The function, $f(\bullet)$, can be any positive integrable function, such as, an exponential function, an absolute value, a square function, etc. $C_{i,t}$ is the continuous deterioration of a component.

A jump in deterioration is used to capture either an extreme event or a non-extreme jump event. An extreme event is a rarely occurring event that causes a severe damage to the system. A non-extreme jump event is a sudden more frequent change that does not cause a severe damage as an extreme event. The arrival of a jump is modeled as a Poisson process. Assuming only one shock can occur in an arbitrarily small period of time, a jump in deterioration can be described as follows.

$$J_{i,t} = U_{i,t} \times I_{\{N_i(t^+) - N_i(t^-) = 1\}}, \tag{5.4}$$

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where $I_{\{N_i(t^+)-N_i(t^-)=1\}}$ is an indicator function indicating a jump of a component, $N_i(t)$ is the number of jumps up to time t, which follows a Poisson process with a rate λ_i, and $U_{i,t}$ is the intensity of the jump at time t of component i.

The overall deterioration of the product is the combination of the two deterioration processes, continuous deterioration and occurrence of jumps as shown in Equation 5.5.

$$D_{i,t} = C_{i,t} + J_{i,t}, \tag{5.5}$$

where $D_{i,t}$ is the deterioration level of a component i at time t.

The deterioration of the system can be derived from its components as follows.

$$D_{sys,t} = \sum_{i=1}^{N}\sum_{j=1}^{N}\sqrt{\rho_{ij}D_{i,t}D_{j,t}} + J_{sys,t}, \tag{5.6}$$

where $D_{sys,t}$ is the deterioration of the system at time t. N is the number of components, ρ_{ij} is the intensity of functional connection of components i and j, and $J_{sys,t}$ is a jump in deterioration of the system.

Equation 5.6 provides an insight for the analysis of the engineering reliability of a product [161], but it comes at a tremendous computational costs because it requires tracking the evolution of each component's deterioration. Since this chapter focuses on the evaluation of contract properties based on the framework proposed in [162] where risks and appropriate setups of LTSAs outlined in Figure 5.1 are incorporated, applying Equation 5.6 will be difficult and computationally expensive. Thus, we need a more parsimonious model tracking system deterioration that statistically converges to the system deterioration calculated from Equation 5.6 in each period without having to track each component.

To create the more parsimonious model (system model), we need to appropriately fit a parsimonious process to the deterioration process found in Equation 5.6. Similar to the component-based model (Equation 5.6), the system model consists of two parts, i.e., a continuous deterioration and a jump in deterioration. The continuous deterioration of the system ($C_{sys,t}$) is found similar to Equations 5.2 and 5.3 where the increment of the continuous deterioration is a function of an Ito process. The parameters used to calculate $C_{sys,t}$ for the system model (i.e.,

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$\alpha(C_{sys,t}, t)$ and $\beta(C_{sys,t}, t))$ are estimated from the first term of Equation 5.6, i.e., $\sum_{i=1}^{N}\sum_{j=1}^{N}\sqrt{\rho_{ij}D_{i,t}D_{j,t}}$. A jump in the system deterioration is found by using Equation 5.4, where corresponding parameters (λ_{sys} and $U_{sys,t}$) are estimated from $J_{sys,t}$ in Equation 5.6. The system deterioration is calculated by combining the two terms similar to Equation 5.5. The detailed analysis of the mapping and parameter estimation can be found in Appendix B.

We have developed a continuous deterioration model with jumps used to infer the evolution of the health of the product in this section. Next section will focus on box 2 of Figure 5.2, where we develop maintenance models under condition based maintenance strategy.

5.3.2 Maintenance

This section focuses on developing models pertinent to maintenance (box 2 in Figure 5.2). Maintenance is aimed to retain the product in a good functional state and to minimize failures or malfunction of the product, since failures or malfunctions of the product result in disruption of production, reduction in quality of product's outputs, and/or severe loss of lives and/or capital. In general, the provider sets pre-specified trigger events of both components and the system so that it can detect a "suspicious" or a "prone to failure" state of the system before the system succumbs to failures. In this chapter, trigger events are identified corresponding to the deterioration level of the system and determine the optimal maintenance action for each trigger level. A maintenance action is considered if the deterioration level of the system increases to specified trigger zones. This section starts with identifying trigger events, followed by a construction of maintenance actions. After a list of maintenance actions is created, corresponding models, which estimate components involved in an action, find effect of an action, calculate maintenance cost and times for maintenance, are developed.

5.3.2.1 Identifying Trigger Events

The system consists of several components which degrade randomly over time. Trigger zones are pre-specified by the provider so that the provider can detect warning signs before a component and/or the system breakdown. The trigger zones are

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identified by observing the system deterioration calculated by Equation 5.6 when the components and the system succumb to suspicious conditions and/or failures. For a certain specific choice of the drift and the diffusion of the deterioration model, the result shows that nine values of the system deterioration presented in Table 5.1 define trigger events. At these levels of the deterioration, components and/or the system start falling into warning and/or failure states.

Table 5.1: The threshold levels for trigger events

Trigger events (T_e)	1	2	3	4	5	6	7	8	9
Deterioration level	140	135	133	130	128	123.5	121.5	118.5	113.5

5.3.2.2 Enumerating Maintenance Actions

After identifying the trigger events, an appropriate maintenance action is assigned for each trigger. A list of candidate actions is created similar to the construction of candidate actions discussed in Section 4.3.2 with a minor modification due to the fact that we do not retain any information regarding to the condition of the components. As a result, we collectively refer to the neighbor of a primary part by using the level of the intensity of the interaction between components (ρ). The candidate actions play a critical role in the risk assessment and management framework, since the service delivery highly depends on the choice of maintenance actions. The provider should select maintenance actions such that it can strike a balance between cost of maintenance actions, cost of failures, and system's downtime.

Table 5.2 displays the building block for constructing maintenance actions for the system. Maintenance actions are divided into two types, i.e., a primary action and a secondary action. The primary action is a maintenance primarily aimed to maintain components in a suspicious condition and/or in failure, while the secondary action is an opportunistic maintenance action which is aimed to further improve the condition of the system.

From Table 5.2, the column titled "No. of components" indicates how many components are involved in the primary maintenance action. The numerical value '0' represents "do nothing". The columns titled "Type" and "Action" indicate the type of components and an action the provider chooses to perform, respectively.

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Table 5.2: Description of candidate maintenance actions

Primary action			Secondary action		
No. of components	Type	Action	Neighbor type	Type	Action
Every	Any	Replace	N/A	N/A	N/A
3	Critical	Repair	$\rho > 0$	Any	Replace
2	Non-critical		$\rho \geq 0.5$	Critical	Repair
1				Non-critical	
0					

The provider distinguishes between critical and non-critical components. The column titled "Neighbor type" represents the type of neighbor the secondary action is performed on. If a component i and a component j are functionally connected, they are neighbors. Mathematically, the components i and j are neighbors if ρ_{ij} or ρ_{ji} is greater than zero. This is because the failure of a component i highly affects the condition of components downstream ($\rho_{ij} > 0$ where j is the component downstream). The deterioration of components upstream contributes to the failure of component i ($\rho_{ji} > 0$ where j is the component upstream). It should be noted that ρ_{ij} may not be equal to ρ_{ji}, since component i may not affect component j to the exact same degree as component j affects component i.

5.3.2.3 Estimating the Number of Components Involved in a Maintenance Action

All maintenance actions (A) are composed of a primary action (A_p) and a secondary action (A_s). The number of primary components is found exactly from Table 5.2, but the number of secondary components depends on the number of the neighbors of the primary component(s). As the number of primary components increases, the number of secondary components also increases. A multiplicative model is used to capture the number of secondary components, i.e., $N^i(A_s) = F^i N(A_p)$. F^i is a multiplicative factor of type i neighbor components, $i \in \{c, nc\}$, where c and nc are for critical and non-critical components, respectively. $N(A_p)$ is the number of primary components. Mathematically, $N(A_p) = N^c(A_p) + N^{nc}(A_p)$. The total number of type i components involved in maintenance action A is given by Equation (5.7).

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$$N^i(A) = N(A_p) \times F^i + N^i(A_p), \qquad i \in \{n, nc\}. \tag{5.7}$$

The provider knows how many components are in the product. The neighbor factors can be estimated from the product design. The provider estimates on average how many critical or non-critical components are neighbors of a primary component.

5.3.2.4 Correction Factors for Maintenance Actions and Their Variability

The post-maintenance deterioration of the product is defined using a correction factor model. The provider can choose between repair or replacement of component(s). After implementing a maintenance action, the post-maintenance deterioration level of the system is calculated as follows.

$$D_{sys,t^+} = (1 - CF_A)D_{sys,t}, \tag{5.8}$$

where CF_A is the correction factor of a maintenance action A. Actions comprise of a primary action and a secondary action. Since the secondary action is an opportunistic maintenance, the secondary action enhances the primary action, thus improving the effect of maintenance. The following multiplicative model is used.

$$CF_A = CF_{A_p} \times CF_{A_s}. \tag{5.9}$$

The effect of maintenance needs not be deterministic. Several factors, such as, the condition of repair equipment and experience of maintenance personnel, can contribute to a poor maintenance outcome. Hence, the correction factor (CF) is reduced from the perfect setup of Equation (5.9). The correction factor is modeled as a random variable. The variation of the correction factor of a maintenance action results from an imperfect primary action, an imperfect secondary action, or both. Hence, the correction factor has four outcomes and can be modeled as shown in Table 5.3.

Let $p^g_{A_p}$ be the probability that a primary maintenance action, A_p, is perfect.

$p^b_{A_p} =$ the probability that a primary maintenance action, A_p, is imperfect.

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$p_{A_s}^{b|g}$ = the probability that a secondary action A_s is imperfect given that the primary action is perfect.

$p_{A_s}^{b|b}$ = the probability that a secondary action A_s is imperfect given that the primary action is not perfect.

Table 5.3: Possible outcomes of correction factors of a maintenance action

Primary	Secondary	Correction Factor	Probability
Perfect	Perfect	$CF_{A_p} \times CF_{A_s}$	$p_{A_p}^{g} \times (1 - p_{A_s}^{b\|g})$
	Imperfect	$CF_{A_p} \times CF_{A_s}^{b}$	$p_{A_p}^{g} \times p_{A_s}^{b\|g}$
Imperfect	Perfect	$CF_{A_p}^{b} \times CF_{A_s}$	$p_{A_p}^{b} \times (1 - p_{A_s}^{b\|b})$
	Imperfect	$CF_{A_p}^{b} \times CF_{A_s}^{b}$	$p_{A_p}^{b} \times p_{A_s}^{b\|b}$

5.3.2.5 Maintenance Cost

Maintenance cost is a function of the number of components, component types, and maintenance action. Maintenance cost can be calculated following Equation (5.9), where the maintenance cost is multiplicative combining primary and secondary maintenance costs.

$$C(A) = C(A_p) \times C(A_s), \tag{5.10}$$

where $C(A)$ is the cost of a maintenance action, A. $C(A_p)$ is the cost of a primary maintenance action, A_p, and $C(A_s)$ is the multiplicative factor for the cost of a secondary maintenance action, A_s.

The maintenance cost includes cost of all resources used for maintenance, such as, labor, repair equipment, etc. The maintenance cost of a critical and a non-critical component is an average among all critical and all non-critical components, respectively.

5.3.2.6 Times for Maintenance and Their Variations

Different maintenance actions result in different downtime. The provider has to choose between replacement or repair of component(s). Moreover, the providers can perform an action either on-site or off-site. We assume that an on-site maintenance is done at a customer's site, while an off-site maintenance is done at a provider's repair

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facility. The analysis assumes that replacement of a component can be done faster than repair, since a replacement is to replace an old component with a new one, while a repair is to convert a malfunctioning or suspicious condition to functional condition. The model used to calculate time for maintenance is also multiplicative, where we calculate maintenance time of an action, A, by

$$MT_A = MT_{A_p} \times MT_{A_s}. \tag{5.11}$$

Risk of maintenance time captures delays in the maintenance process. Delays can result from several factors, such as, bad scheduling, resource non-availability, and delays in identifying a problem. Similar to the risks of the correction factor discussed in Section 5.3.2.4, the maintenance time is calculated as a product of perfect or delayed primary maintenance time and perfect or delayed secondary maintenance time presented in Table 5.4.

Let $q^g_{A_p}$ be the probability that there is no delay in maintenance time during performing a primary maintenance action, A_p.

$q^b_{A_p}$ = the probability that there are delays in maintenance time during performing a primary maintenance action, A_p.

$q^{b|g}_{A_s}$ = the probability that there are delays in maintenance time during performing a secondary action A_s given that there is no delay in the primary action.

$q^{b|b}_{A_s}$ = the probability that there are delays in maintenance time during performing a secondary action A_s given that there are delays in the primary action.

Table 5.4: Possible outcomes of time for a maintenance action

Primary	Secondary	Time for maintenance	Probability
Perfect	Perfect	$MT_{A_p} \times MT_{A_s}$	$q^g_{A_p} \times (1 - q^{b\|g}_{A_s})$
	Imperfect	$MT_{A_p} \times MT^b_{A_s}$	$q^g_{A_p} \times q^{b\|g}_{A_s}$
Imperfect	Perfect	$MT^b_{A_p} \times MT_{A_s}$	$q^b_{A_p} \times (1 - q^{b\|b}_{A_s})$
	Imperfect	$MT^b_{A_p} \times MT^b_{A_s}$	$q^b_{A_p} \times q^{b\|b}_{A_s}$

Previously we developed the models for engineering properties and maintenance (boxes 1 and 2 in Figure 5.2). Next section will develop models for service infrastructure (box 3 in Figure 5.2).

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5.3.3 Service Infrastructure

Service infrastructure supports the service delivery of several contracts. The service infrastructure consists of physical components and knowledge-based components facilitating the service delivery. The physical components include a monitoring system, spare part, repair facilities, and human resources. The knowledge-based components include the information systems and information technology supporting the service delivery. Because the service delivery tries to retain the product in its functional state and brings the products back to its functional state if it fails or malfunctions, the quality of service delivery highly depends on the service infrastructure. This section develops risk models for the service infrastructure. Specifically, we focus on the risks of errors in data transmissions and misinterpretation from the monitoring system and an inventory shortage.

5.3.3.1 Monitoring System Model

A monitoring system plays a critical role in supporting the delivery of LTSAs. Products on which LTSAs are extended are usually supported by a sophisticated monitoring system and by condition-based maintenance. The monitoring system helps the provider better assess the condition of the product and, therefore, make better maintenance decisions. The detailed discussion of the function of a monitoring system can be found in Section 3.2.4.

The deterioration calculated by the monitoring system may not truly represent the real condition or the health of the product. Consequently, it may lead to improper maintenance actions and higher maintenance costs. In general, errors in the monitoring systems come from three main sources, e.g., errors in sensors, errors in data transmission system, and software errors at the control center. These errors are of Type I or Type II kind; Type I error corresponds to when the monitoring system interprets the condition of the product as good, but it in fact is not. Hence, the true condition of the product is worse than it is perceived. Type I error can be caused by several sources, such as, errors in sensors or algorithmic errors, delays in data transmission, and delays in responses to the problems. In contrast, Type II error is when the monitoring system interprets the condition of the product as bad,

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but it in fact is good. Thus, the actual deterioration of the product is lower than the perceived level. In general, Type II error can be caused by incorrect data due to sensor errors or algorithmic errors in the control center.

Errors in a monitoring system is captured by the fluctuation of threshold levels defining trigger events. This choice of model is justified, since the monitoring system is shared by several LTSAs, and, thus, the risks of a monitoring system will affect all LTSAs it supports. Moreover, the risk of data misinterpretation increases when the deterioration of the product is close to the threshold levels. The model of the risk of a monitoring system is given as follows.

$$T_{e,t} = \hat{T}_e + \epsilon_{e,t}, \tag{5.12}$$

where $T_{e,t}$ is the observed level of a trigger event e at time t. $\hat{T}_e$ is the true level of the trigger (as shown in Table 5.1), and $\epsilon_{e,t}$ is the level of error (misinterpretation) of a trigger e at time t. The error process is modeled as a Markov chain whose states are identified by the level of error. For instance, we take $\epsilon_{e,t} \in \{-13, 0, 4\}$, and $\epsilon_{e,1} = 0$. The transition probability matrix for this process is given by

$$P = \begin{pmatrix} 0.15 & 0.85 & 0 \\ 0.04 & 0.87 & 0.09 \\ 0 & 0.75 & 0.25 \end{pmatrix}. \tag{5.13}$$

With this transition probability, on average we see 4% of trigger events to be errors of Type II and 10% of Type I. The state space for the sensor process should be set so that the real behavior of an error-prone monitoring system is observed. In general, if the monitoring system is error-prone, maintenance cost is increased due to improper maintenance actions where relatively severe actions, for example Triggers 1-3 in Table 5.1, are activated significantly more than by a non error-prone monitoring system.

5.3.3.2 Inventory Model

The level of inventory significantly affects the downtime of the product, since maintenance actions can be performed if and only if there are parts available in the

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inventory. Therefore, the provider needs to control the inventory level such that an inventory shortage and the total inventory cost are minimized.

Let I_t^i be the number of type i components in the inventory at time t.

$N^i(A_t)$ =The number of type i components involved in the maintenance action A at time t.

R_t^i =The number of type i components repaired at time t.

P_t^i =The number of type i components purchased at time t.

The inventory evolution model is as follows:

$$I_{t+1}^i = I_t^i - N^i(A_{t+1}) + R_{t+1}^i + P_{t+1}^i, \qquad i \in \{c, nc\}. \tag{5.14}$$

In general, components are refurbished after they are removed from the product and are sent for repair at a repair facility. In our analysis, we assume that the repair time is negligible, since our analysis considers only one contract. In general, the provider sells several LTSAs, and the size of the inventory pool supporting all the contracts is larger than the inventory level that we consider in our analysis. Components are salvaged if they are not sent to repair and are used up to their allowable usage level. Let $F^{i,s}$ be the average fraction of type i components salvaged. The number of type i components refurbished at time t can be found as follows.

$$R_t^i = (1 - F^{i,s}) \times N^i(A_t), \qquad i \in \{c, nc\}. \tag{5.15}$$

Let C_h^i and C_P^i be the holding cost and the purchase cost of a type i component, respectively. The inventory cost at time t can be computed as follows.

$$C_t^H = \sum_{i \in \{n, nc\}} (C_h^i I_t^i + C_P^i P_t^i). \tag{5.16}$$

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5.3.3.3 Relationship between the Level of Inventory and Delay of Downtime

In this section we focus on the delay in performing a maintenance action due to inventory shortage. Since we retain only information about the type of components, we cannot precisely track if components in the inventory are the components that we need for maintenance action (A). We capture the waiting time due to inventory shortage, W_t, by comparing the number of components we need for the maintenance action ($N^i(A)$) with a fraction of the current inventory level. If the fraction of the inventory level is less than the components needed $N^i(A)$, it is highly likely that the shortage occurs. The waiting time due to the inventory shortage, W_t, is modeled as follows:

$$W_t = \begin{cases} 0 & \text{if } 0.7 \times I_t^i \geq N^i(A), \\ U(1,7) & \text{otherwise.} \end{cases} \tag{5.17}$$

The total downtime DT_A of maintenance action A is the sum of maintenance time of action A (discussed in Section 5.3.2.6) and the delay due to inventory shortage, W_t.

$$DT_A = MT_A + W_t. \tag{5.18}$$

This section developed models pertinent to service infrastructure (box 3 in Figure 5.2). In particular, we discussed an inventory model, which finds the evolution of inventory level and a monitoring system model, where we capture the behavior of the monitoring system through the fluctuation of threshold levels for trigger events. In the next section, we will focus on developing a model which aims to evaluate the provider's performance as required by the contract.

5.3.4 Contract Definitions

LTSAs are well-crafted contracts between a provider and a customer. The contract definitions are usually complex due to the nature of sophisticated, high-cost, and long-lived products. Therefore, the provider and the customer co-create a contract in order to clearly identify and define their roles and responsibilities in the service delivery. In general, a contract covers financial obligations, engineering

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and functional deliveries, and legal bindings. The financial obligations and also penalty fee structures relate to the price and the payment plan for a contract. The engineering aspects concern the functionality of the product, where the provider guarantees the functionality of the product in terms of performance measures and maintenance/operations protocols or constraints. The performance measures can be, for example, the throughput, the availability of the product, etc. The legal bindings define contract duration, effective date, liabilities of both parties, extreme-event clauses, etc.

5.3.4.1 Modeling Performance Measures

The performance of the product in terms of its functionality is measured using performance measures. To create the performance measures, the provider and the customer co-define what are measured and how to measure. The performance measures can be a single performance measure or a combination of several performance measures, e.g., availability, throughput, etc. In our analysis we assume that the provider guarantees the level of availability and throughput to the customer, since the product of these two quantities can imply the efficiency of the service delivery.

Availability: The availability is the long-term average uptime of a product during a given period [181]. Mathematically, the availability of a product, AV, can be found as follows.

$$av_t = \begin{cases} 1 & \text{if } D_{sys,t} < T_{9,t}, \\ = 0, [t, t + DT_A] & \text{where t=min } \{u : T_{9,t} \geq D_{sys,u} < T_F\}, \\ = 0, [t, t + DT_F] & \text{where t=min } \{v : D_{sys,v} \geq T_F\} \end{cases} \quad (5.19)$$

where av_t is the availability at time t. $T_{9,t}$ is the threshold level of Trigger 9 in period t. T_F is the maximum deterioration of the system (failure state). DT_A is the downtime of maintenance action A, and DT_F is the downtime of maintenance action

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for failures. The total availability during a given period, $AV^{(t_1,t_2)}$, is as follows.

$$AV^{(t_1,t_2)} = \frac{\sum_{t=t_1}^{t_2} av_t}{t_2 - t_1}, \tag{5.20}$$

where $t_2 > t_1$.

Throughput: The throughput of a product is the total number of output units produced in a given period. In general, the throughput highly depends on the condition of the product. The quantity and the quality of output decreases as the condition of the product degrades. Let O_t be the quality-adjusted output produced per day. O_t can, for instance, take the following values.

$$O_t = \begin{cases} 1000 & \text{if } D_{sys,t} < 60 \text{ and } av_t = 1, \\ 900 & \text{if } 60 \leq D_{sys,t} < 90 \text{ and } av_t = 1, \\ 750 & \text{if } 90 \leq D_{sys,t} < 120 \text{ and } av_t = 1, \\ 0 & \text{if } D_{sys,t} \geq 120 \text{ or } av_t = 0. \end{cases} \tag{5.21}$$

The throughput can be found as follows.

$$TH^{(t_1,t_2)} = \sum_{t=t_1}^{t_2} O_t, \tag{5.22}$$

where $t_2 > t_1$.

There are many throughput measures customers care for. For example, a customer who purchases LTSAs for aircraft engines may be interested in the number of take-offs and landings and the total milage an aircraft engine generates over a given period. As a result, the throughput measures can be a multi-dimensional vector.

5.3.4.2 Penalty Fee

Penalty fees are levied if a contract is breached. For instance, the provider sells a gas turbine bundled with an LTSA. If the provider cannot fulfill the service delivery, it will result in a shortage of electricity or a blackout. The customer

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risks losing its end-consumers and a good reputation and/or needs to compensate its end-consumers. Therefore, penalty fee structures are agreed upon in order to limit unwanted incidents and to compensate the customer if the unwanted incidents happen. The penalty fee structures are negotiated between the provider and the customer. The structures can be setup based on two perspectives, i.e., the customer's and the provider's. From the customer's point of view, the customer pays the provider for the service. If the provider cannot deliver the service, the customer risks losing its end-consumers. Hence the penalty fee structures should take into account fees paid by the customer and costs of losing end-consumers. Thus, the customer would want to set the rate of the penalty fee to be as high as possible. On the other hand, the penalty fee is the provider's expense. Therefore, the provider wants to set the rate of the penalty fee structures to be as low as possible.

Let C_i^{PF} be the negotiated penalty fee rate of a performance measure i. The unit of penalty fee is dollars per unit shortage. In our dissertation, the provider guarantees the availability and the throughput of the product. First a penalty fee model for the availability is developed, followed by a penalty fee model for the throughput.

$$PF_{AV}^m = C_{AV}^{PF} \times \max\{0, AV_g - \frac{\sum_{t=30(m-1)+1}^{30m} av_t}{30}\}, \tag{5.23}$$

$$PF_{TH}^m = C_{TH}^{PF} \times \max\{0, TH_g - \sum_{t=30(m-1)+1}^{30m} O_t\}, \tag{5.24}$$

where $m = 1, 2, \ldots, M$, AV_g and TH_g are the guaranteed level of the availability and the throughput, respectively.

In this section, we formulated two performance measure models evaluating the availability and the throughput of the product and their penalty fee structures. Next section will focus on the financial risks which is the top box of Figure 5.2, where we combine costs incurred in the lower boxes (boxes 2-4 in Figure 5.2) and the revenue received from the customer to evaluate a contract in terms of finances.

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5.3.5 Finance

This section concerns the financial risks of the provider (box 5 of Figure 5.2). Financial models integrates the costs incurred in boxes 2-4 of Figure 5.2 and the revenue received. From the financial perspective, the provider conducts three main activities, i.e., collecting the contract premium, paying for the costs incurred during the service contract, and investing the available funds to maximize its profits. This section begins with the discussion of the revenue model for the provider.

5.3.5.1 Revenue and Reserve Fund Models

The revenue model depends on the price and the payment structure negotiated between the customer and the provider. For instance, the customer can pay the premium to the provider on a monthly basis. The revenue model is assumed to have a linear structure in our analysis. Let Y_m be the cash received by the provider in month m.

$$Y_m = a \times m + b, \tag{5.25}$$

where a and b are parameters of the linear model, and $m = 1, \ldots, M$. M is the duration of the contract in months.

Each month the provider can evaluate the surplus/shortfall of the cash flow between the total cost and the revenue. The net cash flow in month m (NCF_m) is given by

$$NCF_m = Y_m - TC_m, \tag{5.26}$$

where TC_m is the total cost in month m. The total costs comprises of maintenance costs, failure costs, inventory costs, and penalty fees (costs incurred in boxes 2-4 of Figure 5.2). Mathematically, the total costs can be written as follows.

$$TC_m = e^{-\delta m}\Big(\sum_{t=30(m-1)+1}^{30m} (C(A_t) + C_F(I_{\{D_{sys,t} \geq 155\}}) + C_t^H) + PF_{TH}^m + PF_{AV}^m\Big), \tag{5.27}$$

where $C(A_t)$ is the maintenance cost at time t. $C_F(I_{\{D_{sys,t} \geq 155\}})$ is the failure cost

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at time t. The failure cost is the operational cost associated with a unique recovery action, where we include only costs of setting up a new system in order for it to be functional. The cost of failures does not include penalty fee such as lawsuits due to loss of lives and property, since lawsuits are treated as extreme events and needed to be analyzed distinctively.

In each period the provider accumulates or depletes its reserve funds. The reserve fund in month m, RES_m, can be found as follows.

$$RES_m = RES_{m-1} + NCF_m. \tag{5.28}$$

Once the reserve fund for each month of the service delivery is determined, we need to construct risk measures to assess financial risk exposure. This will help us construct appropriate objective functions.

5.3.5.2 Risk Measures

This section discusses rigorous risk measures which are used to evaluate long-term risk exposures for the provider. Risk is an important issue for strategic management. The provider needs to find appropriate risk measures which conform to its business strategy. We set four risk measures for evaluating risks for the provider. The risk measures are as follows.

1. **Mean-Variance Measure**: This measure is the traditional measure in the portfolio theory. We use the mean and the standard deviation of the reserve in the terminal month of a contract to calculate the measure. Mathematically, $RM_1 = E(RES_M) - Std(RES_M)$, where RM stands for the risk measure, and M denotes the terminal month of a contract.

2. **The Cumulative Sum of Mean of Reserve-Variance Measure**: In contrast to the traditional mean-variance measure, which is based on the value of the reserve at the end of the contract, this measure takes into account the evolution of the reserve from the beginning until the end of the contract. Mathematically, it can be written as $RM_2 = \sum_{m=1}^{M}(E(RES_m) - Std(RES_m))$.

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3. **The Cumulative Sum of $100\alpha\%$-Value at Risk (VaR)-Variance Measure**: Similar to the previous measure where we take into account the evolution of the reserve, this measure looks at the worst case scenario that the provider can tolerate. $RM_3 = \sum_{m=1}^{M}(VaR_{(100\alpha)}(RES_m) - Std(RES_m))$, where $VaR_{(100\alpha)}$ is the $100\alpha\%$ value at risk which is the 100α percentile of the reserve [358].

4. **The Cumulative Sum of Mean Reserve-The Probability of Negative Reserve Measure**: This measure focuses on the probability that the provider is insolvent. The measure can be calculated as follows. $RM_4 = \sum_{m=1}^{M}(E(RES_m) - \gamma \times P(RES_m < 0))$, where γ is a scaling factor.

We can set an objective function as a weighted average of the above risk measures. Mathematically, $OV = \sum_{i=1}^{4} w_i RM_i$. The weight (w) for the four risk measures are taken as follows: $w = 0.1$, 0.2, 0.5 and 0.2, respectively. In our analysis the VaR-based Measure (RM_3) is the most important, since it summarizes the worst case scenarios the provider can tolerate. Therefore, we assign a weight of 0.5 to this measure. Note that in our analysis, $\alpha = 0.95$. The measure RM_2 and measure RM_4 are given equal importance by giving them equal weight of 0.2. The traditional risk measure (Mean-Variance measure, RM_1) has the lowest weight, since it gives information on risk only at the end of the planning horizon. Other weights can be considered as seen fit.

The building blocks of the framework have been developed by using a bottom-up approach where risks at the bottom levels in Figure 5.2 must be thoroughly understood before we can progress to study risks at the upper levels. The construction of the framework started with creating the deterioration model that finds the condition of the product. After that, we progressed to develop models for maintenance, service infrastructure, and contract definitions, respectively. The contract definitions were created based on the negotiations between the provider and the customer. Finally, the revenue model, reserve fund model, appropriate risk measures and the objective function were formulated to assess the risks of the service delivery. Next section will discuss a technique used to implement the framework and calculate the risks of the service delivery.

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5.4 Simulation Algorithm

This section implements the framework and develops an algorithm to analyze risks of the service delivery. The problem of assessing risks of an LTSA is complex and is not solvable using analytical methods, since the problem involves several stochastic processes and imposes several controls over the deterioration process due to choices of maintenance and the service infrastructure. As a result, we choose to obtain solutions numerically by using continuous simulation techniques. Among the various continuous simulation techniques, we use the Euler scheme [205], since this scheme is simple, yet provides reasonable accuracy.

Figure 5.3 presents a flow chart for the simulation algorithm. First, we develop the problem specification, where we estimate parameters used in the framework. The parameters are the drift ($\alpha(C_{sys,t}, t)$) and the diffusion ($\beta(C_{sys,t}, t)$) coefficients, the arrival rates for the jump process (λ_{sys}) and its intensity ($U_{sys,t}$), correction factors for maintenance actions, costs and times corresponding to maintenance actions, penalty fee and revenue structures. After a complete specification of the problem, we begin the simulation process in box 2 of Figure 5.3, where we find the deterioration of the product.

After finding the deterioration level in each period, the provider needs to check if the deterioration falls in a trigger zone (boxes 3 and 4 in Figure 5.3). The threshold levels that define the trigger events are given by Equation 5.12. If the deterioration does not fall in a trigger zone, we increment the time by one period and go back to box 2 of Figure 5.3. If the deterioration falls into a trigger zone, a maintenance action is needed (box 5 in Figure 5.3). A maintenance action is generated by the maintenance action generator, and the post-maintenance deterioration level is determined using the correction factor model discussed in Section 5.3.2.4. Besides calculating the post-maintenance deterioration, the provider finds the corresponding maintenance cost and downtime, and updates the inventory level. These are discussed in Sections 5.3.2.5, 5.3.2.6, and 5.3.3.2.

The provider assesses the performance of the service delivery every 30 day using the performance measures discussed in Section 5.3.4.1. After the evaluation of the performance measures, the provider can calculate the penalty fee, the total costs

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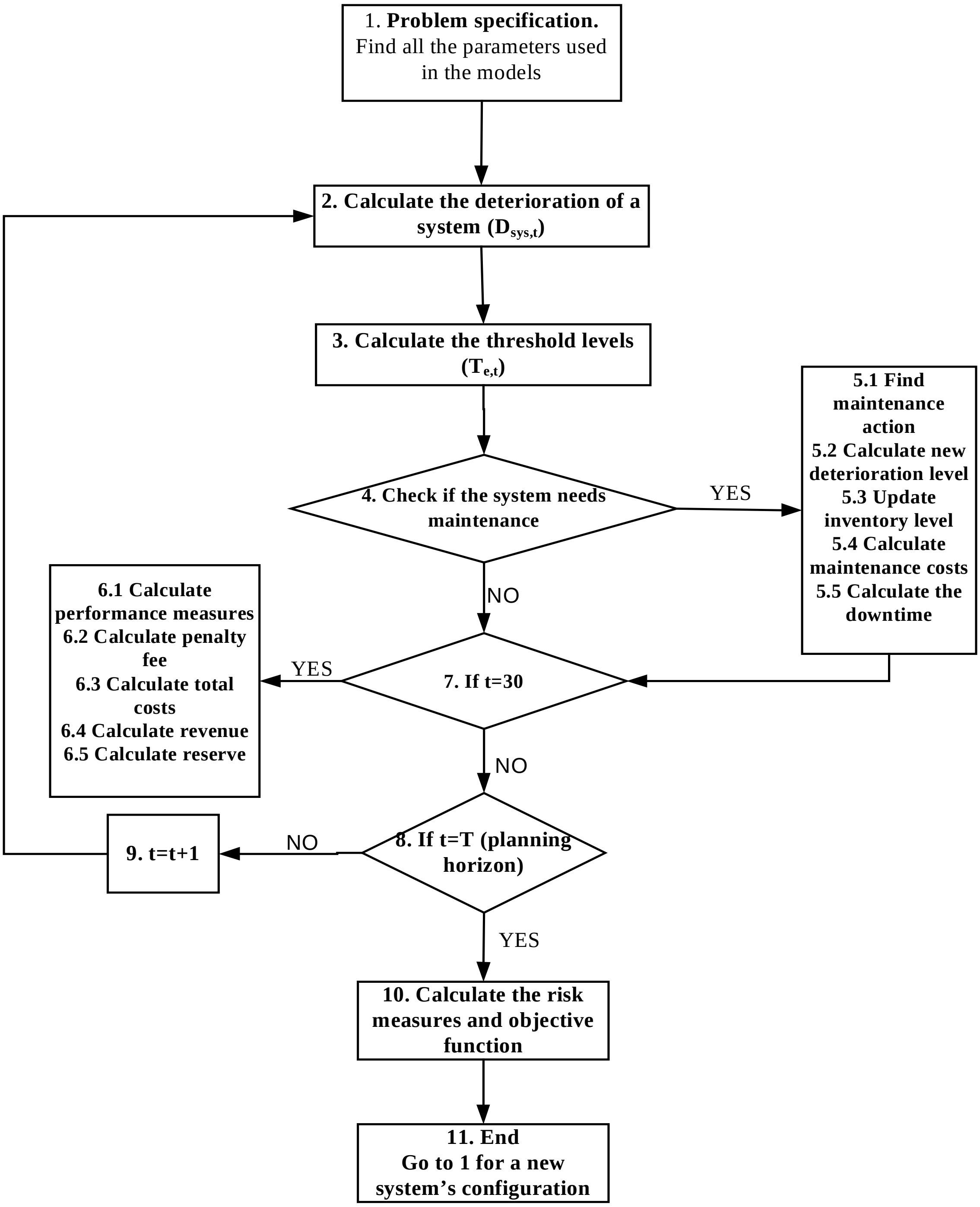

Figure 5.3: Flow chart of a simulation of risk assessment models

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incurred, and the reserve fund in each month. The total costs includes maintenance cost, cost of product failures, inventory cost, and penalty fee. The simulation iterations continue until reaching the planning horizon, T. At the end of the planning horizon, the provider evaluates the risks of the service delivery by calculating the risk measures and the objective function discussed in Section 5.3.5.2.

Next section will demonstrate the application of the framework and the simulation algorithm to find the risks of a service delivery determined using only maintenance costs at the engineering level, since the provider often develops a service delivery strategy by focusing only on minimizing long-term maintenance costs. After the risks of this service strategy is assessed, we attempt to lower the risks by finding appropriate infrastructural setup for the provider.

5.4.1 Analysis of Optimal Maintenance Action Obtained at the Engineering Level

In this section, results are presented to illustrate the implementation of the simulation, where we analyze the risks of the service delivery where the provider develops the service strategy by considering only maintenance costs. The provider finds the optimal maintenance actions which minimize the maintenance costs over the long run based on a detailed engineering properties model [161]. After finding the optimal maintenance action, the provider develops a consistent service strategy based on these maintenance actions. In our analysis, the parameters used in the system model are estimated using the parameters given in the example in [161].

From our estimation, the drift ($\alpha(C_{sys,t}, t)$) and the diffusion ($\beta(C_{sys,t}, t)$) terms are 2.814×10^{-5} and 0.0107, respectively. The arrival rates (λ_{sys}) for jumps per year in the system deterioration are 0.169 for critical components and 0.203 for non-critical components.

The maintenance strategy, developed based on the result found in Chapter 4, is termed $COPT_1$ (Candidate OPTimal), which is described in Table 5.5. After constructing $COPT_1$ to be consistent with the system model discussed in Section 5.3.1, we assess the risks of $COPT_1$ strategy. In our analysis, the planning horizon, T, is 10 years, and Δt is one day. We implement the simulation in $MATLAB$ on a

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Table 5.5: The table describes the $COPT_1$ strategy

Trigger events	Primary Action	Secondary Action
1	Replace every component	N/A
2	Replace every critical component	Replace every neighbor whose $\rho > 0$
3	Replace every critical component	Replace every neighbor whose $\rho \geq 0.5$
4	Replace every non-critical component	Replace every critical neighbor whose $\rho > 0$
5	Replace 3 critical components	Replace every critical neighbor whose $\rho > 0$
6	Replace any 3 components	Repair every neighbor whose $\rho \geq 0.5$
7	Replace 2 critical components	Replace every neighbor whose $\rho > 0$
8	Replace 1 critical component	Replace every neighbor whose $\rho > 0$
9	Replace 1 non-critical component	Repair every component whose $\rho \geq 0.5$

Pentium 4 machine with 3.2 GHz processor and 1 GB memory. We simulate 3000 replications to evaluate the risks of the service strategy, and the run time is around 1000 seconds. The total costs of $COPT_1$ are given in Table 5.6. Note that the inventory cost is calculated using (s, S) inventory reorder policy [177]. The reorder levels (S) are 5 for critical and 10 for non-critical components. The reorder points (s) are 1 for critical and 3 for non-critical components, respectively.

Table 5.6: A cost matrix of $COPT_1$ strategy

	E(Total Cost)	E(Maintenance Cost)	E(Inventory Cost)	E(Penalty Fee)
$COPT_1$	37667	16961	14101	6604

Next, we will enhance our analysis to find appropriate infrastructural setup which can reduce the total cost.

5.4.1.1 Analysis of Optimal Inventory Policy

After finding the costs of $COPT_1$ strategy, the provider can try to optimize the infrastructural setup to reduce other costs, i.e., the inventory cost and the penalty fee. Since the provider does not have a complete control over the penalty fee and its structure, the provider can attempt to reduce the inventory cost. The provider can optimize the inventory cost by searching for an appropriate inventory reorder policy and its parameters. We assume that the provider chooses between the following two inventory reorder policies, i.e., (s, S) policy or (Q, r) policy [177]. (s, S) policy is to reorder $S - x$ parts if the inventory level (x) is lower than s $(x \leq s)$. (Q, r) policy is to reorder Q parts if the inventory level (x) is lower than r $(x \leq r)$. Hence, (S, s) policy limits the maximum inventory level, while (Q, r) limits the maximum number of components purchased.

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Our focus is to find the optimal reorder quantity S for (s, S) policy and Q for (Q, r) policy. We fix the reorder point (s in (s,S) and r in (Q,r)), since the provider in general knows the reorder level which minimizes backorder. We initially set the reorder quantity to be [5,10] for (s,S) and [4,7] for (Q,r), Note that the elements in the vector denote the reorder quantity for critical and non-critical components, respectively. The search begins by fixing the reorder quantity for non-critical components and decreasing the reorder quantity for critical components by 1. Once the total cost stops improving, we switch to fix the reorder quantity of critical components and decrease the reorder quantity of non-critical components by 1. The search then resumes until the total cost stops improving.

The optimal parameters for both policies are shown in Table 5.7. (Q,r) policy with $Q^* = [2, 6]$ is the optimal inventory policy for $COPT_1$ strategy which reduces the total cost from the setup in Table 5.6 by 3.6%.

Table 5.7: A comparison between (s, S) and (Q, r) inventory policy of $COPT_1$

Policy	Optimal Parameters	E(Total Cost)	E(Maintenance Cost)	E(Inventory Cost)	E(Penalty Fee)
(s,S)	$S^* = [4, 9]$	37216	16885	13727	6603
(Q,r)	Q^*=**[2,6]**	37145	16941	13593	6611

Next section will expand our analysis to search for optimal revenue parameters which maximize our objective function.

5.4.1.2 Analysis of Revenue Parameters

In this section, we analyze the revenue model to find the optimal revenue parameters that minimize the risks. The provider has some freedom to control the revenue structure. As a result, the provider can construct the revenue model which minimizes its risk profile. In our analysis we assume that the revenue has a linear form and the provider collects the fee monthly.

To find the optimal revenue parameters, we initially set the slope of the revenue model (a) to be 3 and decrease the slope by 0.5. Since the total discounted fee is fixed, the intercept of the revenue model (b) can be calculated from the total discounted fee and the slope. The search stops when the objective function stops increasing.

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From the search, we found that the optimal revenue parameter are as follows: a^*= -1.5 and b^* = 746. The optimal objective value is \$55420. The optimal revenue parameters are as expected, since we start our analysis with a new system. The linearly decreasing model allows the provider to build up their reserve early in the contract period. Therefore, the provider reduces the risks of insolvency.

Our analysis so far is based on the optimal maintenance action ($COPT_1$) which considers only long-run maintenance costs. Adopting $COPT_1$ strategy, we utilize our framework and our simulation algorithm to find the optimal inventory policy and its parameters and the revenue model to support $COPT_1$ strategy. However, there is no guarantee that $COPT_1$ strategy is the universally optimal strategy that minimizes risks and the total costs, since $COPT_1$ strategy was obtained only from maintenance considerations. Next section analyzes if $COPT_1$ strategy is the optimal strategy when we take into account risks and every other cost dimension.

5.5 Simulation Based Optimization

The costs of the service delivery consist of maintenance cost, inventory cost, and penalty fee. Hence, $COPT_1$ strategy cannot be guaranteed as the optimal service strategy, since it is found just by maintenance considerations. In this section, we enhance our analysis by proposing a search procedure to find the optimal service delivery strategy which considers risks and all the cost aspects.

We begin our analysis to see if $COPT_1$ strategy is a good strategy by comparing it with seven other carefully selected maintenance strategies. When we do not consider service risks in our analysis, $COPT_1$ strategy remains the winning strategy. This is because $COPT_1$ is carefully constructed based on the analysis of optimal actions that minimize maintenance cost. By not considering service risks, we assume that we have a perfect knowledge of the deterioration level of the product, and maintenance actions are perfect. However, when service risks are incorporated (adding the MS model and the risks of maintenance models), there are four solutions or strategies ($COPT_{2-5}$ strategies) that outperform $COPT_1$ strategy. This is because the increments of the maintenance cost and the penalty fee of $COPT_1$ strategy are much greater than those of other four strategies ($COPT_{2-5}$). In other words,

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$COPT_1$ strategy is more sensitive to risks than the other strategies. Therefore, we conclude that $COPT_1$ strategy is not a universally good strategy, and we need to find the optimal maintenance action, where we take into account every cost aspect and risks.

The objective of finding the optimal strategy is two fold. First is that the best of the four new strategies investigated cannot be guaranteed as the optimal strategy, since these strategies were carefully, but arbitrarily constructed. A rigorous search may find a strategy better than the best of $COPT$ strategies. Secondly, the optimal strategy cannot be completely different from $COPT_1$ strategy because $COPT_1$ strategy is constructed from a more detailed analysis where we derive the deterioration of a system and maintenance actions from the evolution of the deteriorations of its components. Completely moving away from $COPT_1$ strategy may be impractical.

The rigorous search procedure adopts a two pronged approach. It combines a directional search with an evolutionary algorithm. Figure 5.4 pictorially outlines the search algorithm. The first part is to create neighbor solutions for $COPT_i$ and $COPT_j$ strategies by adopting a directional search (creating circle around $COPT$s in Figure 5.4), and the second part creates candidate solutions in a dumbbell region around two parents by applying an evolutionary algorithm to identify fit children of the parents (creating dumbbell (cylinder) between $COPT$s in Figure 5.4). Details of the search algorithm are as follows.

Let A be a set containing candidate solutions, $COPT$.

ObjA = A set containing the objective value (total cost) of the candidate solutions in A.

BestAction = A set containing the best solutions.

BestObj = A set containing the objective value of solutions in $BestAction$.

P(C) = A set of primary actions of a solution, C.

S(C) = A set of secondary actions of a candidate solution, C.

NH = Neighborhood solution of Solution A.

ObjNH = The objective value of Solution NH.

BNH = A set containing the best L solutions of neighborhood.

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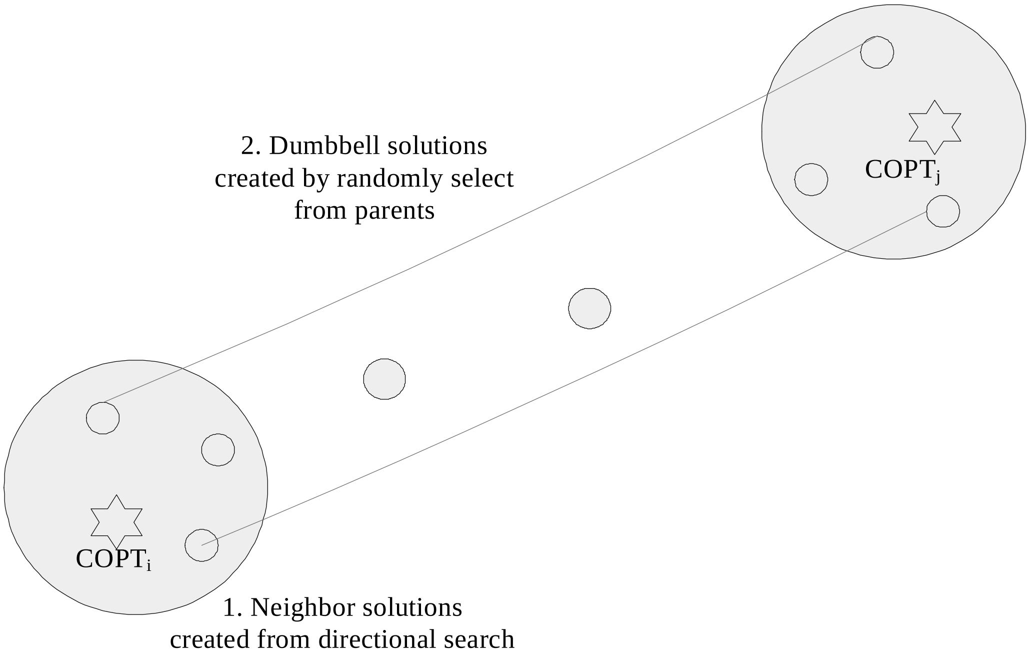

Figure 5.4: The outline of optimal search procedure

ObjBNH	=	A set containing the objective value of the solutions in BNH.
Itr	=	A count of iterations.

1. Initialization

Set $A = 5\ COPTs$ by setting A(1)= $COPT_1$ and ObjA = the total costs of 5 COPTs.

BestAction = A and BestObj = ObjA.

Note we set BestObj(1) = 0 so that we will not update $COPT_1$.

2. Create neighborhood solutions of $COPT_i$ and $COPT_j$

(Circle around $COPTs$ in Figure 5.4).

For each pair wise of $COPT_i$ and $COPT_j$

2.1 Initialize BNH_1, BNH_2, $ObjBNH_1$ and $ObjBNH_2$.

2.2 Find the direction of $COPT_i$ and $COPT_j$.

$D^{ij} = [P(A_j) - P(A_i), S(A_j) - S(A_i)]$.

2.3 Generate K new neighbor solutions of $COPT_i$ and $COPT_j$.

2.3.1 Find the size of the changes of maintenance actions, Δ.

$\Delta^i = unidrnd(min(2, |D^{ij}| + 1)) - 1$.

$\Delta^j = unidrnd(min(2, |D^{ij}| + 1)) - 1$.

2.3.2 Find K new solutions.

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$NH_1 = A(i) + \Delta^i(\frac{D^{ij}}{\|D^{ij}\|})$.
$NH_2 = A(j) - \Delta^j(\frac{D^{ij}}{\|D^{ij}\|})$.
2.3.3 Call simulation routine to assess the objective value
and store in $ObjNH_1$ and $ObjNH_2$.
2.3.4 Evaluate the new NH solutions and retain the best L solutions
in BNH_1 and BNH_2 as a parent for the evolutionary algorithm in the next step.

3. Create a combination (dumbbell) of the neighbors of $COPT_i$ and $COPT_j$ (Cylinder between $COPTs$ in Figure 5.4).

3.1 Select a parent by pairing each solution contained in BNH_1 and BNH_2.
Let X_i and X_j be a maintenance action picked from BNH_1 and BNH_2, respectively.
3.2 Generate a random number for selecting maintenance actions from the parents.
3.3 If the random number is less than 0.5, select a maintenance action from X_i:
Else select a maintenance action from X_j: End if.
3.4 Evaluate the new maintenance action and update $BestAction$ if necessary.

End

Set $Itr = 0$.

4. Create a combination of $COPT_1$ and $BestAction$

While $A \neq BestAction$

4.1 Set $BestAction = A$, set $Itr = Itr + 1$.
4.2 Repeat step 3 with the following slight modification in step 3.3.
For r=2 to length(BestAction)
If the random number is less than 0.5,
select a maintenance action from $COPT_1$.
Else we select from $BestAction(r)$: End if.
End for r.

End and return the optimal maintenance action.

Note that in step 4, $COPT_1$ strategy is always selected as a parent because the optimal solution cannot be completely different from $COPT_1$ strategy.

In the search, we create 3 neighbor solutions for each $COPT$ in step 2 and retain the best two solutions of the neighbor solutions. In step 3, we create four

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new solutions for each pair of parents. Hence, in steps 2 and 3 we create 100 new solutions. In each iteration of step 4, we create 8 new solutions. The algorithm stops after the second iteration of step 4 by when we have explored a total of 116 maintenance strategies. The simulation is implemented in $MATLAB$ and runs for about 30 hours on a Pentium 4 machine with 3.2 GHz processor and 1 GB memory. The optimal solution (OPT) is described in Table 5.8.

Table 5.8: The table describes the OPT solution

Trigger events	Primary Action	Secondary Action
1	Replace every component	N/A
2	Replace every critical component	Replace every neighbor whose $\rho > 0$
3	Replace every critical component	Replace every neighbor whose $\rho \geq 0.5$
4	Replace every non-critical component	***Replace every neighbor whose*** $\rho > 0$
5	Replace 3 critical components	Replace every critical neighbor whose $\rho > 0$
6	Replace any 3 components	Repair every neighbor whose $\rho \geq 0.5$
7	Replace 2 critical components	Replace every neighbor whose $\rho > 0$
8	Replace 1 critical component	Replace every neighbor whose $\rho > 0$
9	***Replace 1 any component***	Repair every component whose $\rho \geq 0.5$

The optimal maintenance strategy is not completely different from $COPT_1$ strategy, where actions corresponding to only two triggers are different from each other. We highlight the different actions in Table 5.8. The OPT strategy is more aggressive than the $COPT_1$ strategy, where we perform more aggressive primary maintenance action for Trigger 9 and more aggressive secondary action for Trigger 4. OPT strategy significantly reduces the number of triggers activated. Hence the maintenance cost is reduced. Moreover, since there are fewer maintenance events for the OPT strategy, the exposure to the risks of maintenance under OPT strategy is lesser than the exposure to the risks of maintenance under $COPT_1$ strategy. This results in lower inventory costs and penalty fees. Hence, OPT strategy outperforms $COPT_1$ strategy in every cost aspect.

OPT strategy results in a 5% reduction in the mean total cost from $COPT_1$ strategy. In particular, the maintenance cost, the inventory cost and the penalty fee under OPT strategy are 7%, 1% and 12% less than those under $COPT_1$ strategy. From the penalty fee, we can conclude that OPT strategy improves the service quality for the provider, since the penalty fee is significantly reduced.

OPT strategy cannot completely move away from $COPT_1$ strategy as completely moving away from $COPT_1$ might be infeasible in practice. Thus, OPT

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strategy may not be a truly global optimum because we restricted the search space and because a truly global optimum maybe impractical. The quality of OPT strategy can be ensured by comparing it with the lower bound of the total cost. The lower bound of the total cost can be obtained from the analysis of $COPT_1$ strategy when service risks are not taken into account, since the service delivery is ideal when there are no service risks and since $COPT_1$ is the optimal solution found when we did not take into account service risks. As pointed out earlier, if we did not take service risks into account, $COPT_1$ was a winning strategy. However, $COPT_1$ was sensitive to service risks compared to the other solutions. We reported the total cost of the lower bound in the third row of Table 5.9 title "LB". The OPT solution is only 7% increment from the lower bound solution. Since the lower bound solution is not achievable in the presence of service risks and since OPT solution is considerably closed to the lower bound solution, the OPT solution is a very good solution.

Table 5.9: A cost comparison between $COPT_1$ and OPT solutions

	E(Total Cost)	E(Maintenance Cost)	E(Inventory Cost)	E(Penalty Fee)
OPT	35592	15819	13962	5811
$COPT_1$	37667	16961	14101	6604
LB	32977	14474	13430	5073

Costs of $COPT_1$ and OPT strategies in the initial setting when the inventory reorder policy is (s,S), s=[1,3], and S=[5,10], are given in Table 5.9. Similar to the analysis of $COPT_1$, we further minimize risks by finding the optimal inventory policy and its parameter and the optimal revenue parameters for OPT. The search procedure to find the optimal inventory policy is similar to the one discussed in Section 5.4.1.1 for $COPT_1$, where we search to find the optimal S^* for (s, S) and Q^* for (Q, r) policies. Based on the search procedure, we find the optimal parameters and compare the results under both inventory policies. Table 5.10 presents the optimal parameter values and the cost differences between the optimal (s, S) and (Q, r) policies.

From Table 5.10, we find that the total cost is less when the (s, S) policy is adopted with $S^* = [4, 8]$. On average, (s, S) policy yields a lower inventory level than (Q, r) policy. As a result, (s, S) has a lower inventory cost but higher penalty fee.

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Table 5.10: A comparison between (s, S) and (Q, r) inventory policy of OPT

Policy	Optimal Parameters	E(Total Cost)	E(Maintenance Cost)	E(Inventory Cost)	E(Penalty Fee)
(s,S)	$S^* = [4, 8]$	35314	15830	13621	5863
(Q,r)	$Q^* = [3, 6]$	35526	15841	13901	5784

The inventory cost and the total cost are reduced by 2.4% and 0.7% from those shown in Table 5.9. It should be noted that while we reduce the inventory cost, the penalty fee slightly increases, since we increase the possibility of an inventory shortage. As a result, the product availability is reduced and the penalty fee increases.

The mean total costs from the two inventory strategies are close. Thus, we need to perform a hypothesis test if the mean total costs are statistically different. We conduct the test at a significance level of $\alpha = 0.05$. The hypothesis testing does not reject the null hypothesis. Therefore, we can conclude that the two means of the total costs are not statistically different. The standard errors of the (s,S) and (Q,r) inventory policies are 101.88 and 106.93, respectively. Since there is no statistical difference between the expected costs of the two inventory policies, the provider may opt to choose (Q,r) inventory policy as it is the optimal inventory policy when no service risks are included.

After optimizing the total cost, we find the optimal revenue parameters similar to the analysis discussed in Section 5.4.1.2 for $COPT_1$. From performing this search, we find that the optimal price parameter values for OPT are as follows, a^*= -2.0 and $b^* = 776.75$. The optimal price parameters are as expected, since we start the system as new. Hence, the linearly decreasing model allows the provider to build up its reserve funds early in the contract duration. The objective value is \$70626. This is a 27% improvement on the objective function when compared to $COPT_1$.

We have analyzed the risks of the service delivery of an LTSA for the provider. The analysis began with finding the risks of the service delivery strategy which optimizes only long-run maintenance costs ($COPT_1$). The result showed that when risks and all cost aspects are incorporated, $COPT_1$ is no longer the winning strategy. Hence, we proposed a search algorithm to find a strategic optimal maintenance strategy which takes into account risks and every cost dimension. The search algorithm combines a directional search with an evolutionary algorithm. Once we

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found a strategic optimal service strategy that minimizes total cost and risks, we further enhanced our analysis to find an appropriate infrastructural setup to further decrease costs and risks. In the next section, we study an impact of a monitoring system to the service delivery, since maintenance decisions highly depend on the accuracy of the monitoring system.

5.5.1 Sensitivity Analysis of the Monitoring System

We now focus on the sensitivity analysis of the monitoring system. The monitoring system plays a vital role in the service delivery. Since the provider relies on the information obtained from the monitoring system to make important maintenance decisions, the accuracy of monitoring systems is essential for effective delivery of LTSA. Moreover, the monitoring system supports several LTSAs. The improvement of the accuracy of the monitoring system, therefore, results in providing better service for a portfolio of LTSAs. In this analysis we set up a more hypothetically accurate monitoring system in order to show the benefits of setting up a more accurate monitoring system in place. The new monitoring system has the following transition probability.

$$P = \begin{pmatrix} 0.15 & 0.85 & 0 \\ 0.025 & 0.90 & 0.075 \\ 0 & 0.75 & 0.25 \end{pmatrix}. \tag{5.29}$$

This transition probability results in 9% and 2% occurrence of Type I and Type II error events, respectively. Overall this transition probability improves the accuracy of the monitoring system by around 5%. Equipped with the new monitoring system in place, the provider further reduces the total cost by 2.65% (from \$35314 to \$34071) compared to the optimal setting in Table 5.10. The maintenance cost and the penalty fee are \$15120 and \$5716, which are reduced by 4.5% and 2.5%, respectively. The objective value is \$115290 which is a 63% improvement from the optimal setting discussed in Section 5.5.

It is expected that a more accurate monitoring system reduces the costs and risks of the service delivery. This sensitivity analysis supports the argument by

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showing that improving the accuracy of the monitoring system helps the provider enhance the quality of the service delivery (since the penalty fee is reduced), reduces the maintenance cost, and significantly reduces the risks even for a slight improvement in the accuracy (5%). The sensitivity analysis of the monitoring system encourages the provider to bring a more inventively accurate monitoring system in place to constantly improve the quality of the service delivery, reduce risks and costs, and increase the profits.

5.6 Conclusions

This chapter develops a rigorous quantitative framework to analyze risks of service delivery of long-term service agreements. The main focus of the framework is the quality of the service delivery attributed from several important risk dimensions from the provider's perspective. The risk dimensions include risks of engineering reliability of a product, risks of maintenance, risks of service infrastructure, risks of contract definitions, and financial risks. Appropriate risk measures are created to assess the risks of a service strategy.

The framework is solved using a continuous simulation. We implement the framework to assess the maintenance strategy which takes into account only maintenance costs ($COPT_1$). Other strategies are constructed to compare with $COPT_1$. When we consider risks of the service delivery, inventory costs, maintenance costs, and penalty fees, the result shows that $COPT_1$ is no longer the winning strategy. Hence, a sophisticated search algorithm is proposed to find strategically optimal maintenance action (OPT) which minimizes risks and the total costs. After finding the optimal maintenance action, we enhance the analysis by finding optimal service delivery setup which minimizes costs and risks. In particular, the optimal inventory policy and their parameters and the optimal revenue parameters are found.

The framework is applied to a sample product where the service strategy found using the framework can be used as guidelines for strategic service practices along with imposing directions for tactical service operations. The optimal service strategy (OPT) found recommends more aggressive maintenance actions than the service strategy which considers just maintenance costs ($COPT_1$). Since OPT is more

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aggressive, there are fewer maintenance events for OPT. As a result, OPT is less exposure to the risks of maintenance and has smaller total cost than $COPT_1$. Besides the reduction in the total cost, the result found that OPT strategy considerably improves the service quality for the provider, since the penalty fee under OPT is significantly reduced than that under $COPT_1$.

This chapter found the service operations strategy for optimal delivery of LTSAs where post-installation risks are incorporated. The framework helps the provider better understand the interrelation between different sources of risks of the service delivery. However, risks are not totally eliminated. There are some risks, e.g., financial risks, to which the provider is exposed. Financial risks are absolutely vital to the provider as they concern the provider's ability to pay for the service. The provider, therefore, needs to reduce its financial risks by taking advantage of financial instruments to develop an appropriate hedging strategy. This problem of financial management will be discussed in the next chapter.

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CHAPTER 6
Optimal Strategic Financial Management Minimizing Shortfall of Cash Flow for the Provider of Long-Term Service Agreements

We identified potential sources of risks in Chapter 3 and started to develop a risk management framework from product risks in Chapter 4. In Chapter 5, we analyzed the interrelations of different sources of risks and found the optimal maintenance strategy for an LTSA and its optimal infrastructural setup for the provider. The frameworks developed in previous chapters aim to reduce strategically operational risks. However, the provider is still exposed to several risks, e.g., financial risks and extreme-event risks. This chapter develops a financial framework which minimizes financial risks for the provider. The framework further reaps benefits of the optimal service management developed from last chapters to help the provider analyze its financial risk exposures systematically and better mitigate the risks of the service delivery.

6.1 Introduction

In previous chapters, we developed a framework which helps the provider better understand and quantify its risk exposure and justify its use of its resource to mitigate risks over the long term. The framework begins by identifying important sources of risks in Chapter 3. After complete comprehension of risks of the service delivery, we created the optimal maintenance strategy minimizing long-term maintenance and failure costs from product risks in Chapter 4. Chapter 5 finds the optimal long-term service delivery strategy for the provider. However, the developed frameworks in previous chapters focus on strategic operational level and, thus, cannot totally eliminate every risk faced by the provider. The provider is still exposed to several sources of risks, especially, risks of cash flow.

Risks of cash flow are a mismatch between costs and revenues. The provider

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collects its revenue monthly and needs to pay for the costs of the service. The risks of cash flow occur when the costs exceed the revenue received. As a result, the provider does not have enough cash flow to pay for the service and cannot be able to maintain the level of its service provided. If the shortfall happens very often, this will eventually lead to poorer service, higher penalty fees, fewer customers, and more extreme events happening due to poor service. It will inevitably become a downward spiral until the provider is bankrupt.

There are several causes leading to a shortfall of cash flow. The provider may underestimate its expected total cost as well as its revenue. It is also possible that an extreme event occurs and, therefore, leads to extremely high costs of service beyond what the provider has previously forecasted. In Chapter 5, we attempted to find the optimal service delivery strategy which would yield an accurate estimation of the total costs. Moreover, we have searched for appropriate revenue parameters trying to minimize some financial risks. However, the risks of cash flow have more dimensions than our analysis performed in last chapter.

The risks of cash flow have two main dimensions. The first is when the cash flow becomes negative, and the second is how long it will stay negative. There are several techniques that are used to reduce these two dimensions of the cash flow risks, e.g., asset liability management and hedging strategy. An asset liability management problem tries to match assets with liabilities by investing in various financial instruments, while a hedging strategy is developed in order to reduce risks of the investment portfolio held by the provider. A brief review on these techniques is provided in Chapter 2.

The problem of managing cash flow of the provider of LTSAs is similar to that of insurance companies and pension funds. Insurance companies collect premiums from their customers and need to pay for contingency claims to their customers. Similarly pension funds need to pay benefits to retirees after collecting money from their customers. The function the LTSA provider performs is similar to that of pension funds, since the costs of the service delivery which are paid by the provider can be seen as the benefits retirees receive from pension funds. Meanwhile, LTSAs can be seen as an insurance on products that guarantees the pre-specified level

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of functionality. The provider needs to pay penalty fees to their customer if the products cannot function as specified in the contract. This is similar to an insurance company, where the insurance company needs to pay for contingency claims to their customers. The provider needs to pay for the costs of service delivery and penalty fees while receive flows of revenue. To effectively manage assets and liabilities, insurance companies, pension funds and LTSA providers take advantage of different risks of their customers' contacts or plans and of yields and volatilities of financial instruments in order to create an inexpensive investment portfolio that matches assets with liabilities over a long period [51, 192, 218, 291].

In this chapter, a framework for financial management is developed. The framework concentrates on building a hedging strategy which minimizes risks of cash flow and achieves maximum profit at the end of the contract. The framework exploits the results obtained from Chapter 5 where we use the revenue model and the total costs found in Chapter 5 to develop a hedging strategy aiming to minimize the shortfall of cash flow.

The problem of developing the hedging strategy deals with finding an investment decision in selected assets to reduce the shortfall of cash flow and to yield maximum profit. The provider collects the revenue from its customer and pays for the service costs for the customer monthly. The provider accumulates the surplus/loss over time. The accumulation of surplus or loss is called operational reserve. Ideally, the provider would want its operational reserve to be at worst equal to zero. If the operational reserve is negative, it means the provider cannot pay for the service. Hence, a shortfall occurs. To avoid the shortfall, the provider can prudentially invest its surplus in financial assets in order for the surplus to be appreciated over time and can cover the shortfall.

The rest of the chapter is organized as follows. Section 6.2 describes the problem in detail including with some preliminary analyses. Section 6.3 demonstrates how assets are selected. In Section 6.4, we formulate the problem of developing a hedging strategy. We propose a simulation algorithm and discuss the results of the simulation in Section 6.5 We end the chapter with our conclusions in Section 6.6.

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6.2 Problem Description

The provider sells a long-term service agreement to a customer. By selling the agreement, the provider is responsible for providing necessary services and paying for the service costs, e.g., costs of spare part and labor costs, in order to deliver the required functionality of the product for a specific period. In return, the provider receives revenue from its customer. We assume that the provider collects its revenue and pays for the costs of the service in monthly basis. In each month the provider finds its cash flow which is the difference between costs and revenue. Since the revenue is deterministic while the cost is stochastic, the cash flow varies widely. The provider accumulates an operational reserve, which is the cumulative cash flow. The operational reserve indicates whether the provider conducts its business successfully, since the positive operational reserve indicates the profit for the provider. In contrast, the negative operational reserve indicates the loss to the provider. The financial problem for the provider arises when the operational reserve becomes negative (i.e., the shortfall occurs) as the provider does not have enough fund to pay for its service.

In order to minimize the shortfall, the provider needs to invest its surplus (positive cash flow) in appropriate assets in order for them to be appreciated in the future and can cover future losses. The first question is what are appropriate assets the provider should invest in. In order to answer the question the provider needs to estimate when the shortfall is likely to happen, since some assets, such as, bonds and options, are priced according to their times to maturity. Without knowing when the shortfall occurs, the provider cannot find appropriate assets which can cover its shortfall successfully. After finding I appropriate assets, the provider prudentially decides a proportion of its surplus (α_i) to be invested in selected assets. The return of the assets (R^i) varies over time depending upon the market value. The objective function is to minimize shortfall risks as well as to maximize the profit at the end of the contract.

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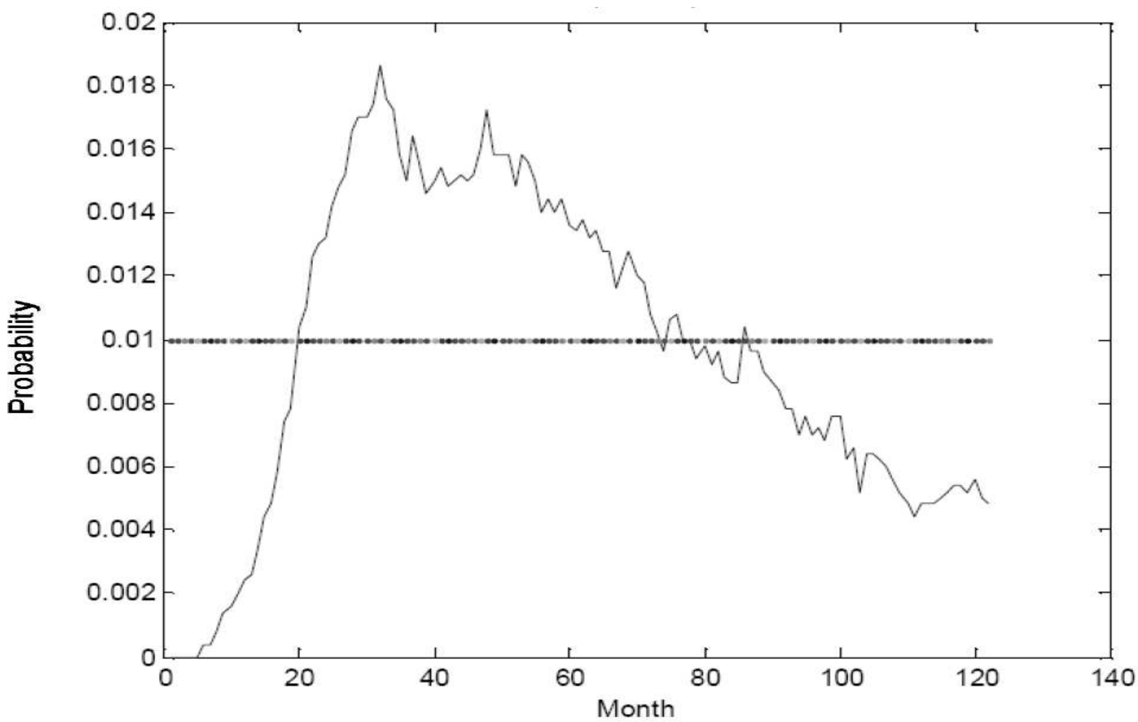

Figure 6.1: The probability of the operational reserve less than zero

6.2.1 Preliminary Analysis

We demonstrate how the asset allocation can reduce the shortfall risks in this section. We begin the section by analyzing the shortfall risks given that the provider does not invest in any financial instruments.

Consider a case where the provider sells a 10-year long-term service agreement. The provider receives the revenue monthly. The revenue model has a linear form where the slope is -2.0 and the y-interception is \$776.75. These parameters are obtained from the analysis in Section 5.5 The costs of the service include maintenance costs, inventory costs, and penalty fees whose parameters can be found in Chapter 5. The monthly cash flow is the residual between costs and revenue, while the monthly operational reserve is the accumulated cash flow. Risks of cash flow occur when there is not enough money to pay for the service or the operational reserve turns negative. As a result, the provider needs to minimize the probability of shortfall.

Figure 6.1 illustrates the probability of shortfalls faced by the provider in 10 years. The shortfall probability is relatively low. The maximum probability of

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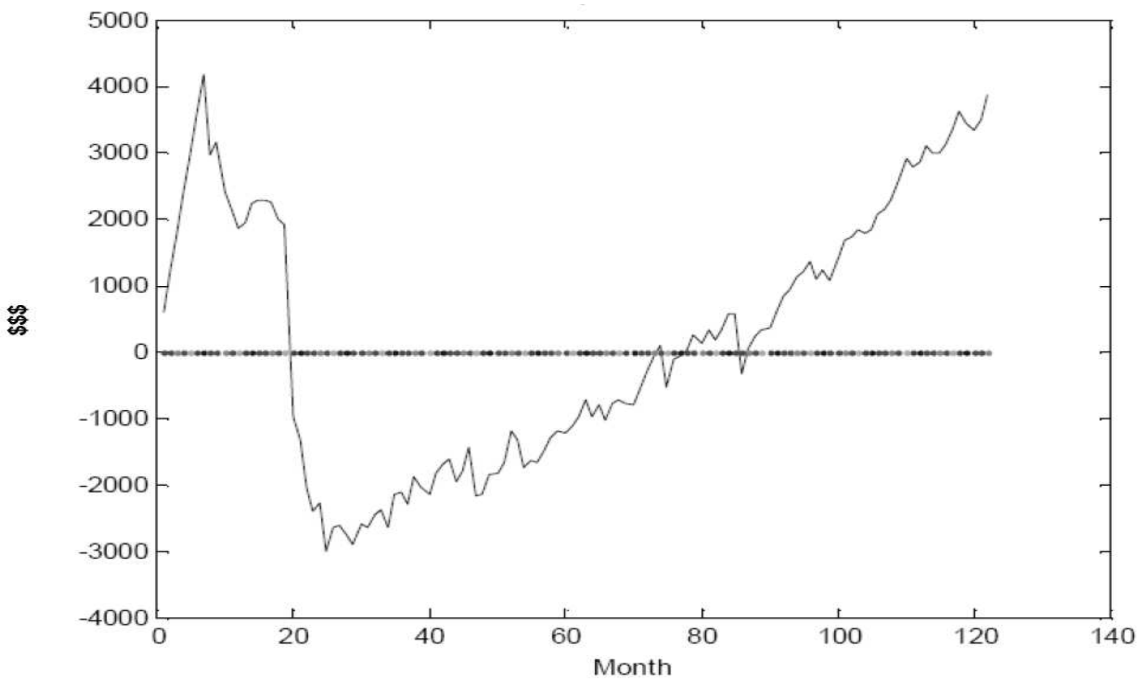

Figure 6.2: 99% Value at Risk of the operational reserve over time

getting shortfall is 0.0186 occurred in period 32. In another word, the maximum chance that the provider is in debt is less than 2%. There are 57 periods in which the shortfall probability is at least 0.01. Though the shortfall probability is relatively low, the number of periods the shortfall occurs is high where it is almost 50% over the 10-year period that the probability of shortfall is greater than 1%.

Nocco and Stulz [280] offered a new interpretation of risks where risks need to take into account a firm's reputation as well as financial issues. Reputation is very important for the provider. It relates to how customers perceive a firm's service quality, financial stability, and good prosperity. Failures of products due to poor service can result in catastrophic effect on products, service delivery process, and society. Moreover, they heavily affect the provider's reputation and financial status. The provider needs to take into account reputation into its risk dimension. Though reputation is hard to determined, Nocco and Stulz gave a guideline of credit rating for a firm in term of default risks. The guideline provides a relationship between probability of default and credit ratings. Applying the guideline, we can rate the provider as *Ba* grade, since its default risks is around 1%.

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We present the 99% value at risk of the operational reserve ($VaR_{0.99}(RES)$) which represents the first percentile of the operational reserve we can obtain each month in Figure 6.2. The minimum 99%VaR is around -3000, while the maximum 99%VaR is around 4000. It is obvious from Figure 6.2 that the provider collects handsome profit early in the beginning of the contract when the costs are relatively small and at the end of the contract when the provider has built up its operational reserve. With proper risk management, e.g., transferring funds from early of the contract or at the end of the contract to where the shortfall occurs, the shortfall risks can be significantly reduced.

One simple way to reduce the shortfall risks is to carefully invest in financial investments. We demonstrate this technique by investing the positive operational reserve in appropriate financial assets. To illustrate the use of financial securities, we consider two cases.

1. The provider invests its surplus only in bond which pays 4% annual interest rate.

2. The provider invests its surplus in the stock market. The provider invests in the Dow Jones Industrial Average index, which is taken to evolve by a geometric Brownian motion.

We present the profile of the shortfall probability and $VaR_{0.99}(RES)$ of these three cases (i.e., no investment, investment only in bond or in stock) in Figures 6.3 and 6.4.

Consider Figure 6.3, we can see that the shortfall probability is significantly reduced from when the provider makes no investment. The maximum shortfall probability when the provider invests its fund is 0.0055. We can also observe that the profile of the shortfall probability when the provider invests in stock is higher than the profile of the shortfall probability when the provider invests in bond.

For $VaR_{0.99}(Wealth)$, we can see in Figure 6.4 that when the provider invests its fund the 99% value at risk has never become negative. 99% VaR when the provider invests in stock is higher than 99% VaR when the provider invests in bond. As a result, we can see that bonds reduce the shortfall probability, however, they

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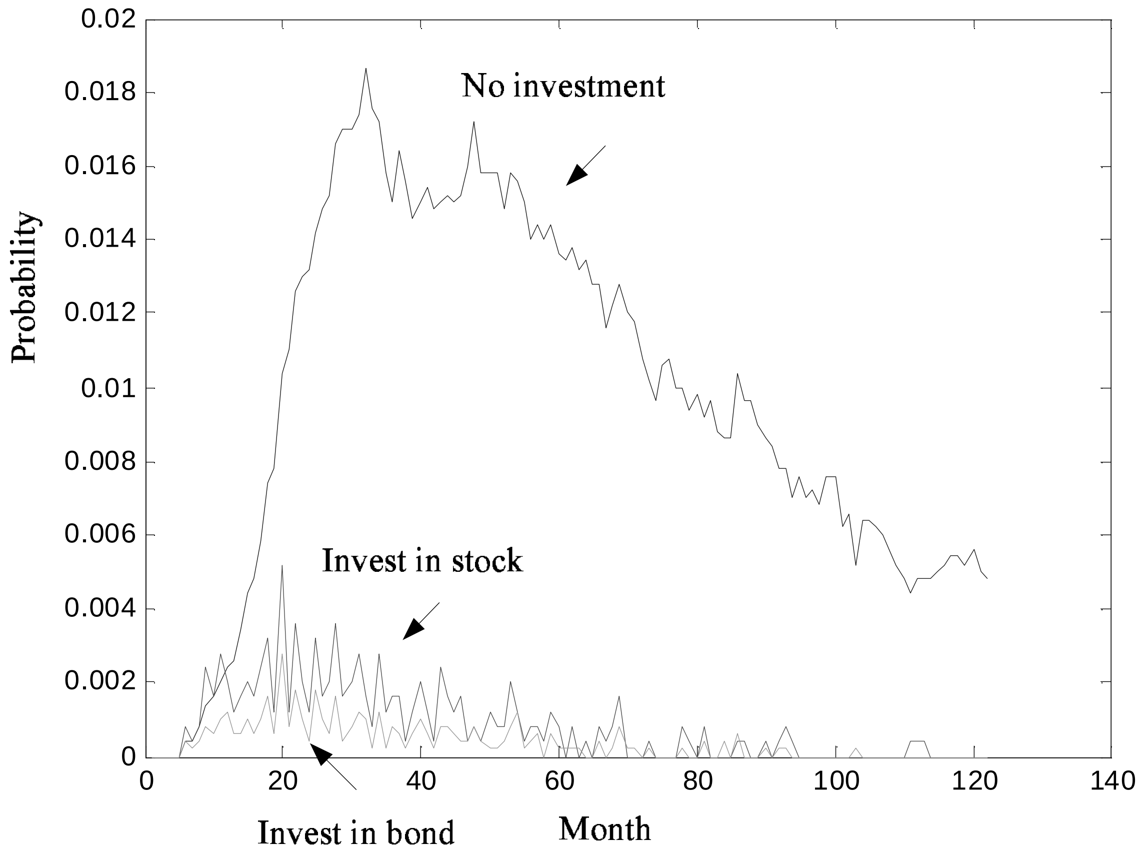

Figure 6.3: The profile of probability that the net worth of the portfolio is negative

generate poorer return than stocks. We report other important statistics between the three strategies in Table 6.1.

Table 6.1: The table compares important statistics between not investing, investing only in stock and investing only in bond

Statistics/Strategy	No investment	Investment in bond	Investment in stock
Mean	2.32×10^4	7.51×10^7	10.78×10^7
Min	-1.21×10^4	2.36×10^3	1.61×10^3
Max	4.14×10^4	1.98×10^9	2.61×10^{10}
Total number of shortfall period	5915	227	512

Note that the statistics reported in Table 6.1 are calculated at the end of the contract period. The total number of shortfall period reports how many periods in 10 years with 5000 replications the provider's wealth becomes negative.

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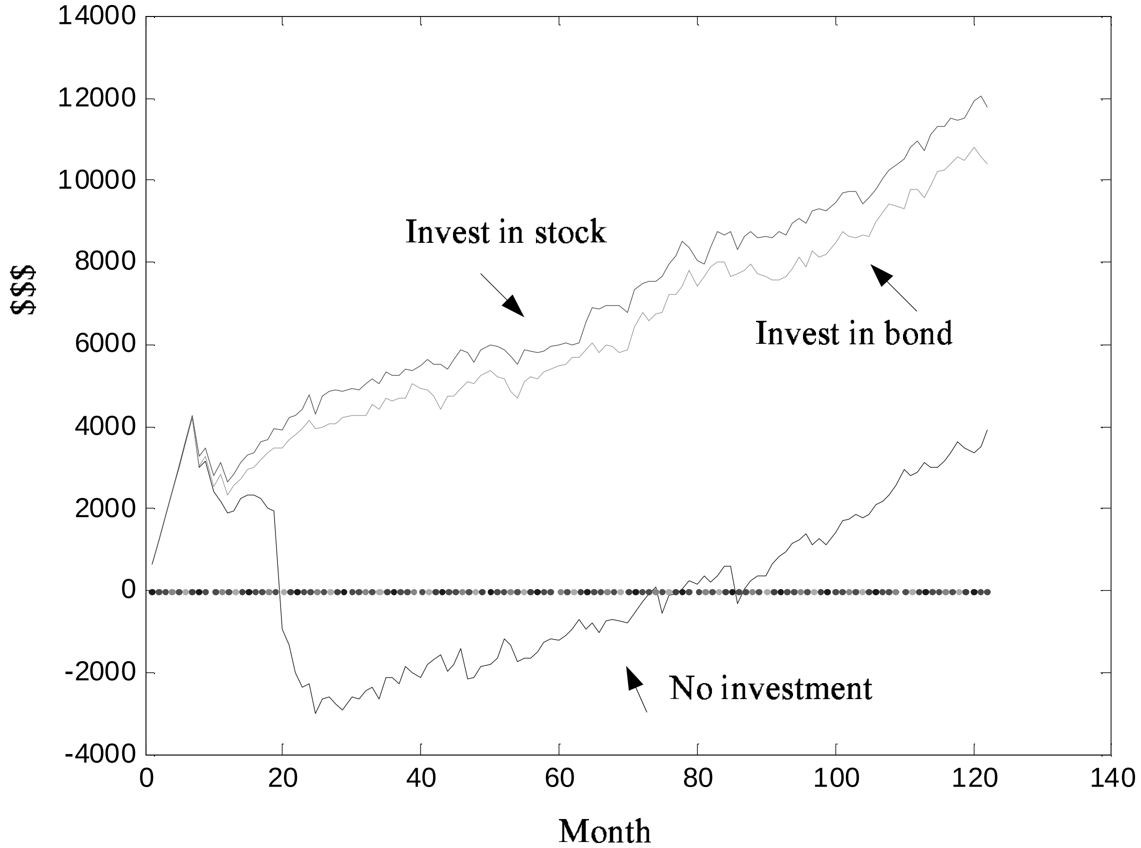

Figure 6.4: 99% Value at Risk of the net worth of the portfolio over time

6.3 Asset Selection

Previously we compare the advantage between different kinds of financial securities. Each type of financial security has different purposes. In this section, we provide a guideline on how the provider selects assets to use in its hedging strategy.

It is evident from our preliminary analysis that investing the provider's surplus in the stock market yields better profit than investing its fund in bond. However, since the stock market is riskier, the probability of shortfall is higher. Nonetheless investing in either asset types results in better outcome than not investing in any financial instruments.

Asset selection strategy is very important. Asset selection decisions pertain to what type and purpose of assets an investor wants them to perform. As a result, the investor needs to understand and carefully define his/her risk exposure, risk appetite, appropriate risk measure and rewards of each asset. Li [227] classifies

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assets for individual into three classes, i.e., protective, market, and aspirational. Protective assets have small risk-return ratio and are used to protect an investor against poverty. While market assets have medium risk-return ratio and maintain an investor his/her living standard, aspirational assets have high risk-return ratio and can enhance an investor's wealth substantially. The classification is also suitable for enterprizes. An enterprize would want to protect itself from shortfall using protective assets, and maintain its level of shareholders value using market assets. Ultimately, an enterprize wants to maximize its shareholder value which can be achieved by investing in aspirational assets.

To appropriately select the right assets, the provider needs to thoughtfully define its risk exposure and risk appetite. We use the following notations to define the shortfall which is the main risk exposure in our problem.

RES_m	=	the operational reserve at time m.
τ_n	=	the n^{th} stopping time where the net reserve is negative.
D_n	=	the duration of the n^{th} shortfall.
X_n	=	the extent of the n^{th} shortfall which is the minimum of the net reserve from τ_n to $\tau_n + D_n$.

6.3.1 Defining Shortfall

In this section, we define the shortfall which quantifies how much deficit the provider incurs.

The n^{th} stopping time of negative operational reserve (τ)

$$\tau_n = \inf \{t : RES_t < 0 \wedge t > \tau_{n-1} + D_{n-1}\} \tag{6.1}$$

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$\tau_0 = 0,\ D_0 = 0$, and n=1,2,...,N.
The duration of the n^{th} shortfall (D_n)

$$D_n = \sum_{t=\tau_n}^{\tau_{n+1}-1} d_t^n \tag{6.2}$$

$$d_t^n = \begin{cases} 1, & \text{if } RES_t < 0 \wedge RES_{t-1} < 0 \text{ or } t = \tau_n, \\ = 0, & \text{Otherwise.} \end{cases} \tag{6.3}$$

n=1,2,...,N.
The extent of the n^{th} shortfall (X_n)

$$X_n = \min RES_m \qquad \texttt{where} \quad m \in [\tau_n, \tau_n + D_n] \tag{6.4}$$

The shortfall is defined as a multiplication between the size $(min(RES_m))$ and its duration. The model is used to emphasize the two most peril of the shortfall which are the size of its negative value and the duration of these negative value. To hedge the shortfall, the provider would want to reduce both the size as well as the duration of negative operational reserve.

6.3.2 Investment Definition

This section introduces some definitions describing the characteristics of the investment problem.

Time of investment: The provider adopts a buy and hold strategy where the provider invests its available money every month.

Time of payoff: The payoff periods of the hedging strategy constructed by the provider will be from $Prctile_{20}(\tau_n)$ to $Prctile_{20}(\tau_n)+Prctile_{80}(D_n)$, where $Prctile_a(A)$ is the a^{th} percentile of A.

We choose the twentieth percentile of τ_n and the eightieth percentile of D_n because judging from Table 6.2 both percentiles seem not to be a decision that is too risk averse but conservative enough to eliminate the shortfall risks. Note that the mean of D_1 is 15 periods. However these percentiles are parameters and are changeable.

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Table 6.2: Percentiles of τ_1 and D_1

Percentile	τ_1	Percentile	D_1
10	17	60	11
15	19	65	12
20	**21**	70	14
25	24	75	17
30	25	**80**	**20**

6.3.3 Selecting Asset

The following assets are selected to used in our model.

1. *Bond*: The bond has a face value of \$1000 whose maturity is shown in the second column of Table 6.3. The selected bond is a US treasury zero-coupon bond, since there is no need for a stream of payments before the maturity date. The bond price can be calculated as follows. $P_{B_t} = P_{B_T}e^{-r(T-t)}$. Thus, $r = -\frac{1}{T}\ln\frac{P_{B_0}}{P_{B_T}}$. The interest rate is calculated from the price of US treasury zero-coupon bonds having 1.5-3 years time to maturity on Apr 11, 2007. The rates of the bonds are presented in Table 6.4.

2. *Large equity stocks*: We invest in the Dow Jones Industry Average index. The stock price follows geometric Brownian motion. $dP_{S_t} = \mu P_{S_t}dt + \sigma P_{S_t}dW_t$. dW_t is the Weiner process. $\mu = 0.091$ and $\sigma = 0.173$. Both rates are per annum. μ and σ are estimated from the index from Jan 1, 1987 to Mar 30, 2007. The initial price (P_{S_0}) is assumed to be \$100.

3. *Protective put options on large equity stocks in 2*: The put options will have a fixed strike price of $0.9P_{S_0}$, where $P_{S_0} = 100$. The maturity is shown in the second column of Table 6.3.

The options are priced using the Black-Scholes model. The price of put options can be found as follows. $P_{O_t} = Xe^{-r(T-t)}N(-d_2) - P_{S_t}N(-d_1)$. $d_1 = \frac{ln(\frac{P_{S_t}}{X})+(r+0.5\sigma^2)T}{\sigma\sqrt{T}}$. $d_2 = d_1 - \sigma\sqrt{T}$. X is the strike price. T is the time to maturity. r is the risk free rate which is 4%. P_{S_t} is the price when the option is purchased, and σ is the volatility which is 17.3%.

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Table 6.3: Time to maturity of bonds and options

Type of assets	Time to maturity
Bonds	1.5 year, 2 years, and 3 years
Put options	1 year

Table 6.4: US treasury zero-coupon bond price as of Apr 11, 2007

Maturity	Price	Days to Maturity	Interest rate
11/15/2008	93.85	584 (1.5 years)	0.039670264
5/15/2009	91.88	765 (2 years)	0.040406124
2/15/2010	89.03	1041 (3 years)	0.040741431

According to the selected percentile parameters, the shortfalls are expected to occur between 2 to 4 years. Hence we should look for assets having intermediate time to maturity. As a result, We select the time to maturity as shown in Table 6.3.

The put options will have strike price equalled to \$90. The payoff curve of the put options is $\max(K - P_{S_T}, 0)$, where K is the strike price which is \$90, and P_{S_T} is a stock price at time T. Bonds and options are automatically renewed once they reach their maturity.

In this section, we developed the problem statement, performed a preliminary analysis, and developed a guideline for asset selection to match the goal of the provider. Next section describes mathematical formulations of the problem.

6.4 Problem Formulation

In this section, we develop our problem formulation when the provider invests its surplus each period. The following notations are used in our problem formulation.

Decision variables

α_i = the proportion of an investment pool assigned for asset i for all time.

State variables

RES_m = the operational reserve in period m.

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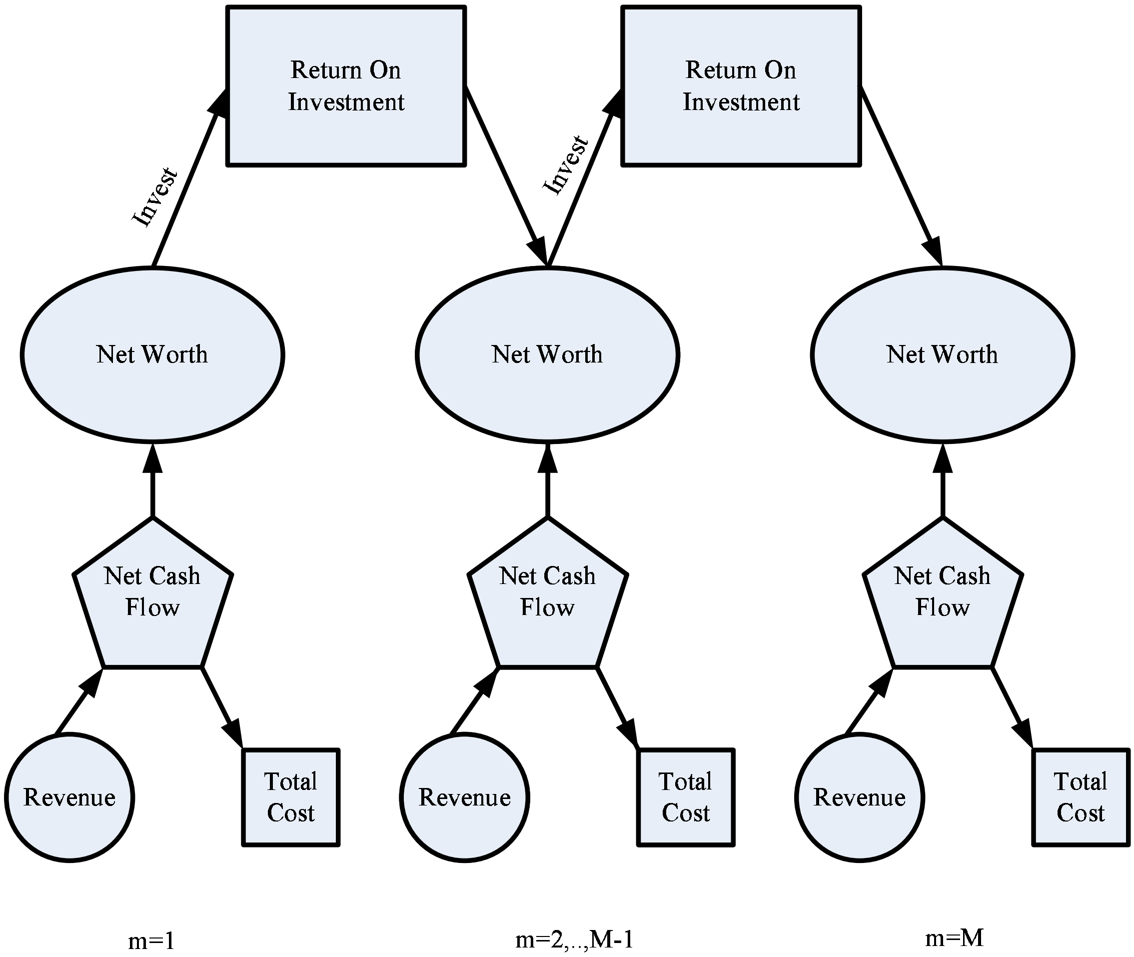

Figure 6.5: The graph represents the flow of the net worth over time

NCF_m = the net cash flow in period m.

$P_{i,m}$ = the price of asset i in period m.

NW_m = the net worth of the portfolio (investment portfolio and operational reserves) in period m.

R^i_m = the return of assets i from period *m-1* to m. $R^i_m = \frac{P_{i,m}}{P_{i,m-1}}$.

Parameters

I = the set of assets. $I = \{B_{1.5}, B_2, B_3, S, O_1, \}$

The subscript is the time to maturity of each assets.

Figure 6.5 illustrates the flow of the provider's net worth over time. The net worth of the provider evolves over time. It depends on the level of revenue, total

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costs and the return on the investment. We develop following equations to be used in the problem formulation.

Net Worth equation finds the evolution of the net worth of the portfolio in every period.

$$NW_m = \sum_I \alpha_i R_m^i NW_{m-1} + NCF_m \tag{6.5}$$

Net worth is the summation of the previous net worth multiplied by the return and the net cash flow (NCF_m)). $NW_0 = \sum_I \alpha_i (NCF_0)^+$. The provider can invest only when the net worth at time $m-1$ is greater than zero. If the net worth is less than zero in period $m-1$, the return will be set to one.

Equation 6.6 finds the evolution of the net cash flow, which is the residual of costs and revenue, over time.

$$NCF_m = Y_m - TC_m. \tag{6.6}$$

The revenue received (Y_m) has a linear form, while the total cost (TC_m) is a function of maintenance cost, failure cost, inventory cost, and penalty fee. We use Equations 6.7 and 6.8 to find the revenue and total cost of the service in each period.

$$Y_m = a \times m + b, \tag{6.7}$$

where a and b are parameters of the linear model, and $m = 1, \ldots, M$. M is the duration of the contract in months. The revenue model and its parameters are obtained from the analysis in Section 5.5 where we search for optimal revenue parameters which minimize aggregated risks of the service.

$$TC_m = CMaint_m + CFail_m + CInv_m + PF_m, \tag{6.8}$$

where $CMaint_m$ is maintenance cost in month m. $CFail_m$ and $CInv_m$ are cost of failure and cost of inventory in period m, respectively. PF_m is the penalty fee charged if the provider cannot deliver required functionality in period m. More detailed calculation and discussion of the total costs can be found in Chapter 5.

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Objective function: The objective function of the problem is to minimize the shortfall as well as maximize the value of the net worth of the portfolio. The shortfall is defined in Section 6.2. In that section, we defined the shortfall in terms of the operational reserve (RES) and performed a preliminary analysis to see how the shortfall looks like.

Since we now combine the operational reserve with the return on investment (portfolio), the shortfall risks occur if the value of the portfolio is below zero instead of caring for only the operational reserve. As a result, we need a little modification for the definition given in Section 6.2 where we replace RES with NW. We denote X_n^{NW} and D_n^{NW} as the measures of the shortfall risks. These two notations are similar to X_n and D_n, but they are found by using the net worth instead of the operational reserve. The shortfall is, therefore, modified as follows.

$$Shortfall = \frac{1}{M} \sum_n E(X_n^{NW}) E(D_n^{NW}). \tag{6.9}$$

The objective function can be mathematically written as follows.

$$\max_{\alpha} VaR_a(NW_M) - Shortfall, \tag{6.10}$$

where $a = 0.99$. VaR of the net worth at the end of the contract provides a good summary of how good the provider manages its service strategy of a contract. The shortfall summarizes the total of the expected negative cash flow over the entire horizon in dollar term.

6.5 Simulation Based Optimization

We present a simulation algorithm used to find the net worth of the portfolio as well as an optimization scheme to find a relatively good asset allocation for the hedging strategy. Finding the net worth of the portfolio involves many stochastic processes, thus, the problem is complex and is hardly solvable using analytical methods. Therefore, we select to obtain solutions numerically using continuous simulation techniques.

We present a flow chart for finding the net worth in Figure 6.6. First, we

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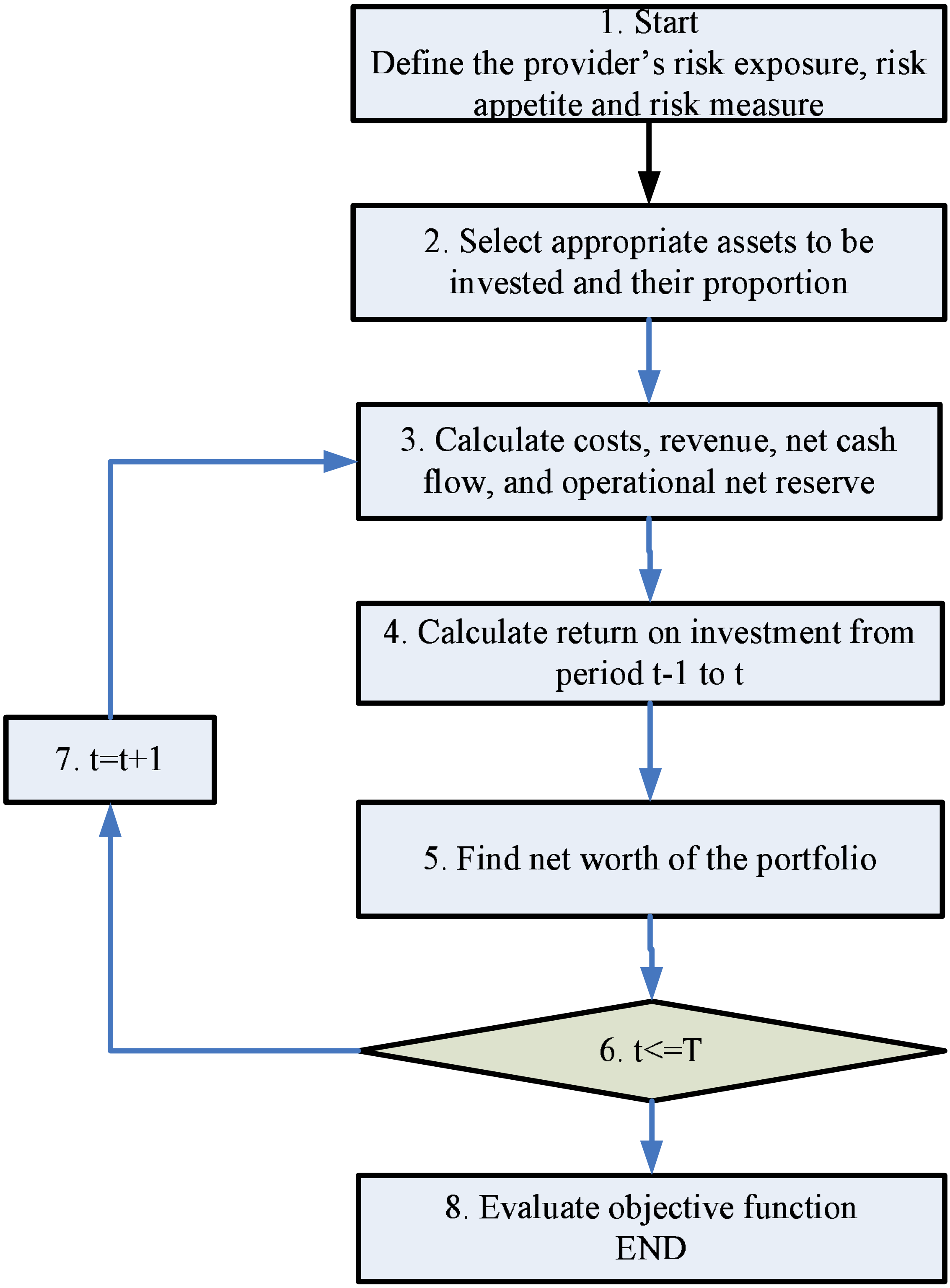

Figure 6.6: Flow chart of the simulation algorithm of asset allocation

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develop the problem specification, where the provider defines appropriate risk exposures, risk appetites and risk measures. This step is very essential. A risk management strategy cannot be used effectively if the provider miscalculates and misjudges its appropriate level of risk exposures and risk appetites. The provider, thus, needs to carefully quantify its suitable level of exposures and appetite. Moreover, the provider has to formulate rational risk measures which well balance between risk exposures and risk appetites.

Once the provider defines its reasonable levels of risks, the provider would want to prudently select asset classes in which the provider wants to invest in box 2 of Figure 6.6. We illustrate how the provider selects asset classes and which assets to be selected in Section 6.3. Besides selecting asset classes, the provider needs to assign right combination of these asset classes to achieve highest return with lowest possible risks.

We begin the simulation process in box 3 of Figure 6.6, where we find the costs, revenue, net cash flow, and operational net reserve. These quantities are direct results obtained from Chapter 5. After finding the net cash flow in each period, we proceed to box 4 of Figure 6.6, where the return on investment from period $t-1$ to t is found. The return on investment depends on the proportion of assets assigned and the level of available fund the provider has.

After finding the net cash flow and the return on the investment, we can find the net worth (wealth or value) of the portfolio in each period by combining the two quantities (box 5 of Figure 6.6). The detailed discussion of how the net worth is found is discussed in Section 6.4. The simulation iterations continue until reaching the planning horizon, T. At the end of the planning horizon, the provider evaluates the financial risks of the service delivery by calculating the risk measures and the objective function discussed in previous section.

In this section, we propose the simulation algorithm which is used to evaluate net worth and finds the objective function. We use simulation techniques to solve the problem because simulation is simple yet provides reasonable accuracy. Next section will discuss a search procedure we adopt to find a relatively good solution.

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6.5.1 Optimal Search Algorithm

The search algorithm is presented in this section. The search algorithm is relatively similar to the search algorithm proposed in Section 5.5. In Section 5.5, we combine a directional search algorithm as well as an evolutionary algorithm. Similarly, the search algorithm in this section combines an evolutionary algorithm as well as a directional search algorithm. However, the directional search in this section is more similar to the search algorithm discussed in Section 4.4.1. The search algorithm tries to span the entire neighbor solution space after initial choices of asset selection is assigned. It attempts to jump to its neighbor if the objective function is improved by the jump. The search for the asset proportion stops if the objective function does not improve or no further jumps are possible for that particular asset (i.e., the proportion is zero or one).

The search algorithm has two main procedures. The first procedure is an evolutionary algorithm where we randomly generate N solutions and create new solutions by mating them together. After that, we select the best Q solutions as parents to use in the next mating process until we achieve the best solution. Note that the number of parents is reducing by q. After finding the best solution, we develop a directional search algorithm where the directional search tries to find if the neighbor around the best solution found in the mating procedure yields better objective function. The order of the search in the directional search algorithm is as follows: bonds (protective), stocks (aspirational) and protective put (market). This is because our primary purpose is to reduce the shortfall. Bonds guarantee the return of the investment which can offset the shortfall. After the shortfall is eliminated through bonds, the provider can increase its net worth through stocks, since stocks create higher yield than bonds. Stocks, while offer upside potential, expose to downside risks due to its higher volatility than bonds. As a result, we search to increase the proportion of protective put in order to protect the provider from downside risks. The algorithm stops if the neighbor around the best solution does not provide any better objective function.

The pseudo code of the search algorithm is as follows.

1. **Initialization**: Randomly generate N solutions.

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Set Q $\leftarrow$ N, IterationCount $\leftarrow$0, and Direction $\leftarrow$ 1.

2. **Mating**.

Do while Q $>$ 1

NewSolutionIndex $\leftarrow$ 0.

for i=1:Q

for j=i+1:Q

Set NewSolutionIndex $\leftarrow$ NewSolutionIndex+1.

Generate NewSolution by mating between Solutions i and j.

Evaluate ObjectiveFunction.

Set IterationCount $\leftarrow$ IterationCount+1.

end for.

end for.

Set Q $\leftarrow Q - q$.

Sort NewSolution and retain the best Q solutions as parents.

end while.

BestSolution $\leftarrow$ Solution.

3. **Directional search**.

Solution $\leftarrow \phi$.

Do while $BestSolution \neq Solution$

If Solution $= \phi$, Solution $\leftarrow$ BestSolution. IterationCount $\leftarrow$ IterationCount+1.

For $k = 1 : TotalAsset$

3.1 **Determining new alpha**

Set $Solution_k \leftarrow Solution_k + Direction \times \delta$.

Set $Solution_{j:j\neq k} \leftarrow Solution_k - Direction \times \frac{\delta}{TotalAsset-1}$.

Set IterationCount $\leftarrow$ IterationCount+1.

3.2 **Update direction**

Evaluate ObjectiveFunction.

If the ObjectiveFunction is improved then

Update ObjectiveFunction and BestSolution $\leftarrow$ Solution

and Direction $\leftarrow$ Direction.

Else

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Set Direction ← (-1)× Direction.

End if.

End for.

End while.

4. Return the solution.

This section discusses the simulation and the optimal search algorithm used in this section. We discuss the results of our finding in the next section.

6.5.2 Results

We discuss the results of the financial investment problem and the performance of the proposed search algorithm in this section.

The evolutionary algorithm attempts to find the best starting point for the directional search algorithm and randomly spans the search to the entire solution space. We randomly create 30 solutions to be used in the evolutionary algorithm. The evolutionary algorithm mates between these 30 solutions to create 465 new solutions in the pool. We select the best 25 solutions from 465 to be seeds for the next mating process. The next mating procedure creates new 300 solutions. We select the best 20 solutions to be parents for the next mating process. Note that we iteratively reduce the pool size of parents by five (q=5). The process continues until we find the best solution to apply for the directional search.

After spanning the search over the entire solution space from the evolutionary search, we select the best solution to be used in the directional search. We pinpoint the directional search to find a better solution around the best solution found from the evolutionary algorithm. We take δ to be equal to 0.001. In total, we create 1232 solutions. The evolutionary algorithm creates 1190 solutions and the directional search creates other 42 solutions. We implement the simulation in $MATLAB$ on Intel(R) Core(TM) Duo CPU machine with 1.86 GHz processors and 1 GB memory. We simulate 5000 replications to evaluate the risks of the service strategy. The total run time of the search algorithm is 102.67 hours. We plot the value of best solutions found from the search algorithm in Figure 6.7. The graph is divided into two sections. The first section plots the best parents found in the evolutionary

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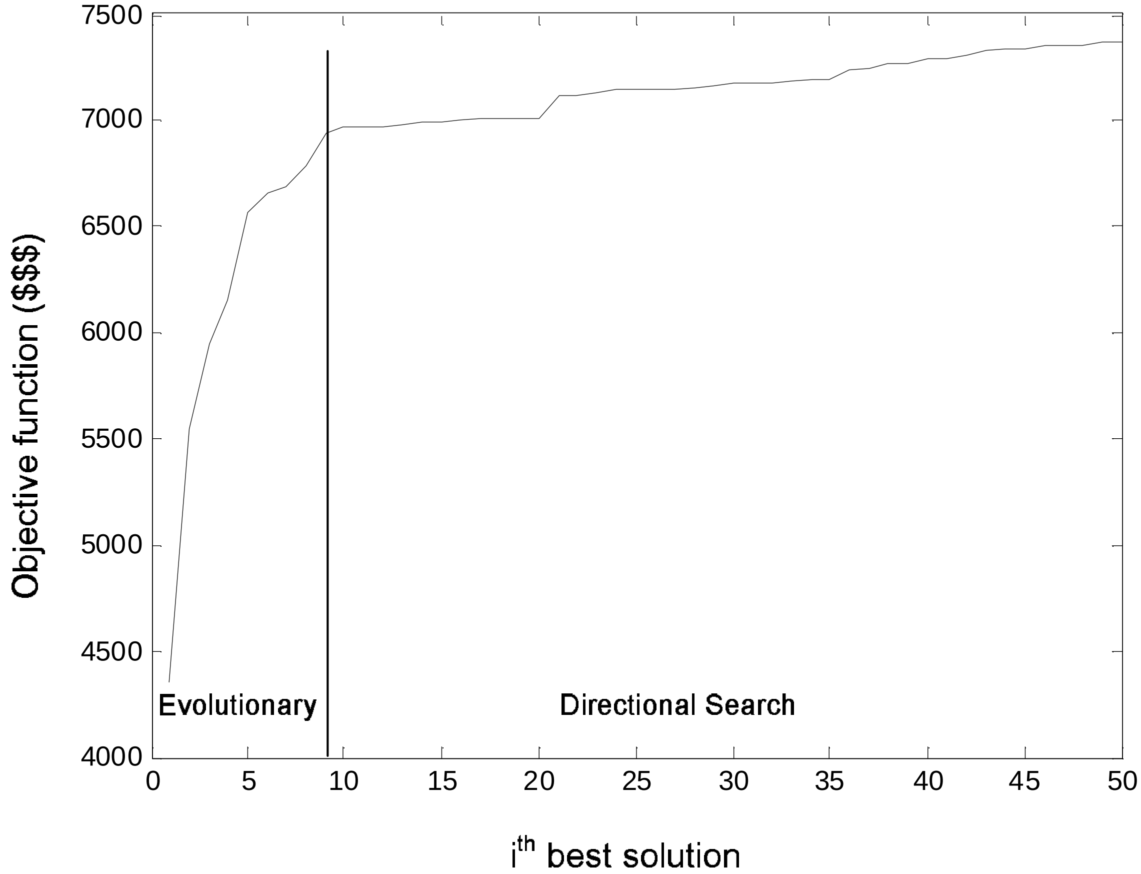

Figure 6.7: A graph plots the evolution of the value of objective function

algorithm before rendering the starting solution of the directional search, which is the best solution found from the evolutionary algorithm. The second panel of the figure plots the improvement from the starting solution after adopting the directional search. We can see significant improvement on the objective value where it increases by almost 8%.

The most favorable asset allocation ($MFAA$) is [0.1625, 0.1850, 0.421, 0.210 0.0215]. The objective value is 7.327×10^3. Our objective function trades off between risks and rewards. The 99% value at risk of the net worth at the end of the planning horizon exceeds the total of the expected shortfall of cash flow of the entire planning horizon by 7.327×10^3. The solution found cannot be ensured as a truly global optimum because the solution space is extremely large and the problem does not have any explicit structure to be exploited to effectively find an optimal solution. Therefore, a truly global optimal solution can only be found from an exhaustive

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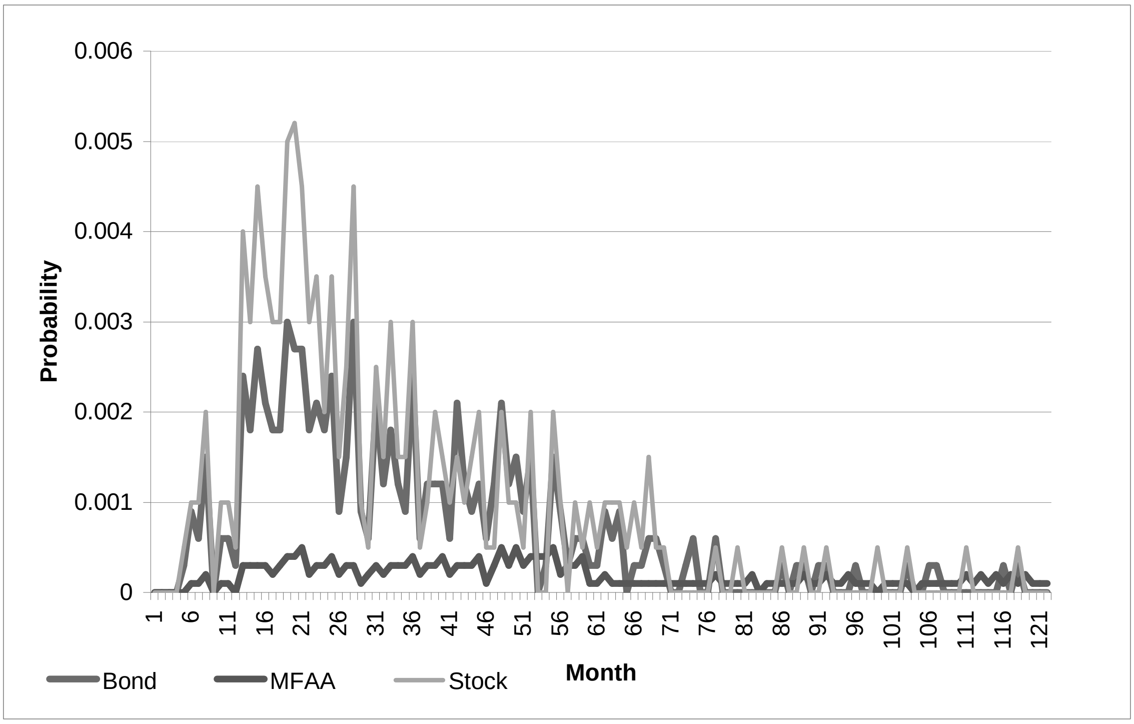

Figure 6.8: A figure compares probability of shortfall of cash flow among various investment strategy and the optimal asset allocation

search.

However, the most favorable solution provides a good quality where it effectively minimizes shortfalls by appropriately transferring positive cash flow to negative areas. Figures 6.8 and 6.9 compare the shortfall probability and $VaR_{0.99}(NW)$ obtained from various investment strategies. We can see from Figure 6.8 that the $MFAA$ solution effectively mitigates risks of shortfall of cash flow, where its probability of negative cash flow is relatively constant throughout the entire planning horizon, while the risk of shortfall of cash flow is very high from period 12^{th} to 30^{th} when we apply other investment strategies.

Table 6.5 compares the objective function and other statistics between various strategies. We can see that the $MFAA$ solution significantly improves the objective function where it increases the objective function by 22.4% and 9.7% from investing only in bond and in stock, respectively. The other statistics obtained from the $MFAA$ solution lie between investing in stocks and in bonds. This is also seen in Figure 6.9 where 99% value at risk of the net worth lies between those of bond

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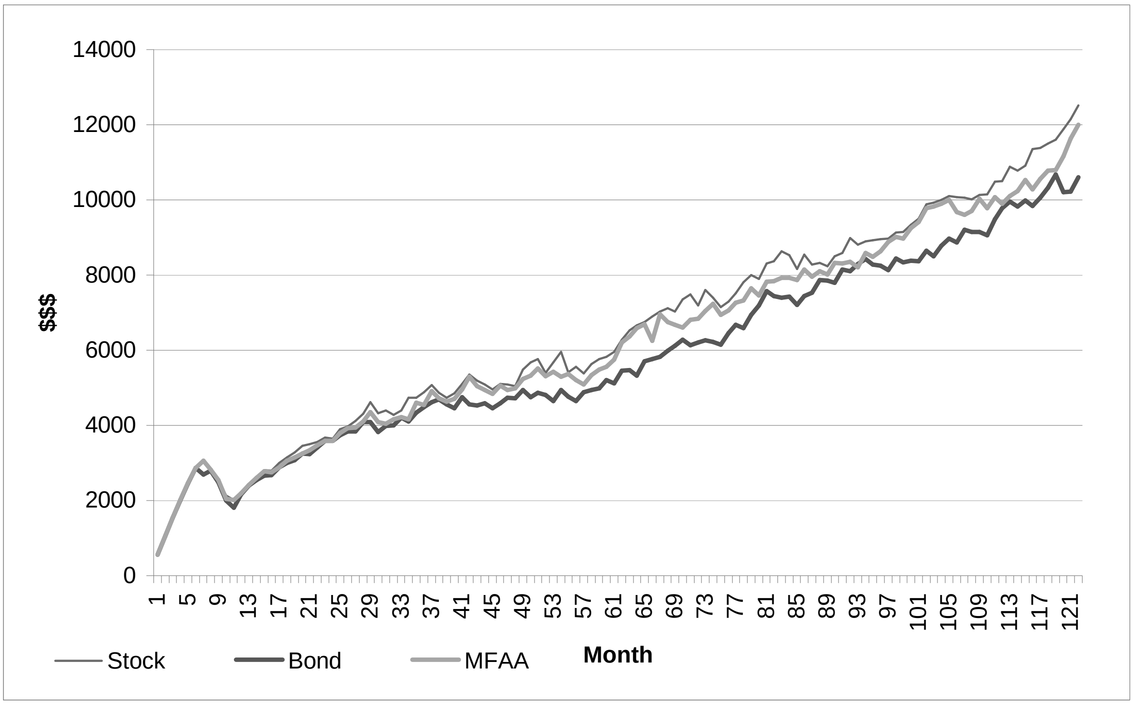

Figure 6.9: A figure compares 99% value at risk of net worth among various investment strategy and the optimal asset allocation

and stock. However, the number of shortfall period reduces tremendously when we invest with our optimal buy and hold strategy.

Table 6.5: The table compares important statistics between investing in the optimal asset mix, investing only in stock and investing only in bond

Statistics/Strategy	$MFAA$ solution	Investment in bond	Investment in stock
Objective function	7.33×10^3	4.99×10^3	5.68×10^3
Mean	9.87×10^7	7.51×10^7	11.40×10^7
Min	1.94×10^3	2.36×10^3	1.61×10^3
Max	3.23×10^9	1.98×10^9	26.1×10^9
Total number of shortfall period	174	227	512

The $MFAA$ solution notably improves the shortfall risks where the total number of shortfall periods is reduced from 227 to 174. The total number of shortfall periods reduces by 23.35%. 174 shortfall periods correspond to 0.03% ($\frac{174}{122\times5000}$) chance that the provider does not have enough cash flow in any period on average. Using Nocco and Stulz's result which studies the transition matrix between default probability among various rating firms [280], the credit rating of the provider is Aa which significantly improves from Ba when we do not consider investment.

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The $MFAA$ solution suggests the provider to invest nearly 80% of its funds in bonds. This is because we highly care for the shortfall risks, and it is obvious from the preliminary analysis discussed in Section 6.2.1 that investing in bonds yields lowest shortfall probability. For the bond allocation, the weight in bonds favors the longest time to maturity bond because it gives highest return. While we invest almost 80% in bonds, we invest only 20% in stock. We invest in stock in order to increase the provider's net worth. From the optimal solution, it is worth noting that the provider holds only a few proportion of the put options. This is because the exercise is fixed at \$90 while the planning horizon of the contract is relatively long (10 years). Therefore most of the times the stock price exceeds the strike price. From our simulation study, there is 10.21% chance that the strike price exceeds the stock prices ($P_{S_m} \leq \$90$) from 5000 replications with a planning period of 10 years. The average stock price provided that it is below strike price is \$77.37. The selected strike price and put model provides sufficient protection for the provider from the downside risks, where the provider can protect itself from highly distressed market risks.

It should be noted that the exercise price of the put option is an input parameter. The provider can select the exercise price depending upon its risk appetite. Changes in the exercise price and put's maturity alter the holding proportion of the put option. Next section discusses a sensitivity analysis of put options to see how optimal asset allocation changes when the strike price of the put changes.

6.5.2.1 Sensitivity Analysis of Exercise Price of Put Option

In our analysis, we have fixed the exercise price of put option to be fixed at \$90. The position of put option is only 2.15% because over the long run the stock price usually exceeds the exercise price. Thus, the provider rarely exercises its put option. In this chapter, we perform the sensitivity analysis where we alter the exercise price of the put.

Table 6.6 reports the sensitivity analysis of the exercise price of the put option. $MFAA_1$ is the most favorable asset allocation found from the previous section, which is $[0.1625, 0.1850, 0.421, 0.2100.0215]$. $MFAA_2$ is a new most favorable asset

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allocation where we obtain after changing exercise price. From the table, we can see that $MFAA_1$ is robust where it obtains the best objective value when the strike price varies from $80-$110. It changes when the strike price becomes relatively low ($70) or very high ($120-$150).

Table 6.6: The table presents the results of sensitivity analysis of put options

Strike price	Objective function of $MFAA_1$ [0.1625, 0.1850, 0.421, 0.210 0.0215]	$MFAA_2$ & Objective function
$70	1.11×10^3	[0.163, 0.1855, 0.4315, 0.2005 0.0190] 1.42×10^3
$80	3.72×10^3	-
$90	7.33×10^3	-
$100	11.18×10^3	-
$110	19.83×10^3	-
$120	26.76×10^3	[0.1435, 0.1775, 0.3545, 0.251 0.0735] 35.42×10^3
$130	42.03×10^3	[0.1435, 0.1775, 0.3545, 0.251 0.0735] 47.29×10^3
$140	59.24×10^3	[0.1435, 0.1775, 0.3545, 0.251 0.0735] 72.94×10^3
$150	74.51×10^3	[0.1435, 0.1775, 0.3545, 0.251 0.0735] 96.32×10^3

Several insights should be addressed from Table 6.6. First, we can see that the strike price has a direct impact on the objective value. Higher strike price yields higher objective value because when the strike price is higher, the provider eminently protects itself from the downside of the market. Thus, the shortfall is reduced and the objective value is higher. Secondly, the optimal put proportion is higher when the strike price is higher, while it is lower when the strike price is lower. Over a long planning horizon, the stock price is unlikely to be lower than a very low strike price. The provider is less likely to exercise its option. Thus, the put option cannot offer much protection to the provider from the downside risks. On the contrary, when the strike price is higher, it is highly likely that the stock price is lower than the strike price. Hence, the provider is more likely to exercise its option making them highly protect itself from diminished return of the stock price and creating higher return on the put option. Therefore, we can see that when the strike price is higher, the proportion of put options held by the provider is higher. Lastly, we observe that higher strike price leads to higher proportion of stock. This is because the provider has higher protection when the strike price is higher. The provider can, therefore, take greater market risks resulting in higher proportion of stock.

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6.6 Conclusions

We develop a framework for an investment strategy where we attempt to find a relatively good asset allocation. The investment problem combines operational risks and financial risks together where the provider would want to invest in assets that can eliminate or significantly reduce its shortfall risks as well as maximize its profit. To solve the problem, we adopt a buy and hold strategy where the provider invests fixed proportion of its wealth to the selected assets and propose an effective search algorithm to find the most favorable strategy. The most favorable asset allocation reduces the shortfall of cash flow and considerably improve the provider's credit rating by upgrading it from Ba when the provider does not invest to Aa when the provider invests in the most favorable asset allocation. The most favorable mix favors bonds, since our objective function is biased toward the shortfall risks and bonds create a guaranteed return to eliminate the shortfall. After applying the most favorable asset allocation, the number of shortfall periods and their extent of shortfall are substantially reduced.

The role of assets in a hedging strategy is very important. The provider needs to carefully choose assets in order to suit its risk appetite. In the framework, we select three zero-coupon bonds, DJIA stock, and a one-year protective put option to be invested. The role of put options is to protect the provider from adverse market risks. The provider can develop more sophisticated hedging strategy, e.g., investing in many put options with different strike prices and maturities or a combination of put and call options. Purchasing several put options with different strike prices with the same maturity greatly protects the provider from a very distressed market, but the provider cannot enjoy the upside return of the market. A combination of call and put options, e.g., a collar option where an investor writes a call and sells a put, allows the provider to take advantage of both call and put options and get protection with least transaction costs. However, the call limits the provider from enjoying upside return. The option strategy depends on the provider's estimation of the future performance of the market. The transaction costs play crucial role in a hedging strategy. The benefit of various options may be negligible after taking transaction costs into account. The framework can be easily extended to include

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the analysis of several options and transaction costs.

Previous chapters focus on strategic risk management where the provider create the optimal service operations and financial risk management strategies to hedge its risks. Next chapter investigates the management of long-term service agreements from operational point of view where the provider attempts to synchronize the decisions made at the strategic business level and to find the optimal maintenance schedule for its products based on these decisions.

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CHAPTER 7
Optimal Part Replacement in a Management of a Portfolio of LTSAs

Previous chapters focus on strategic business management problems, where we find optimal service delivery strategy as well as financial strategy. In this chapter, we extend our work where we streamline the optimal service delivery strategy of an LTSA and extend the decisions to a portfolio of LTSAs. In this problem, our aim is to develop an optimal operations strategy whose cost is minimized.

7.1 Introduction

Typically, a provider sells products bundled with a long-term service agreement. After the products are installed in customers' sites, the providers are responsible for taking care of the products, for which a contract is extended. As a result, the provider develops a maintenance schedule for products, in which it wants to schedule the time for maintaining the products before they breakdown, since the breakdown costs are considerably large compared to maintenance costs. Due to the stochastic nature of the problem, the provider needs to develop the maintenance period based on the reliability properties of the product as well as current condition of the products. Once the condition of the products shows a sign of failures, such as, the output per unit time drops, the quality of the output drops, etc., the provider prevents a breakdown by performing maintenance actions. If parts are replaced, removed parts are sent to repair/refurbishing. After they are repaired, they are re-available for being installed in a product.

The management problem of a portfolio of LTSAs involves several uncertainties and decisions, such as, for maintenance periods, part reliability and repair, crew availability, etc. Thus, modeling the entire problem and solving it all at once is prohibitively hard and needs extremely sophisticated computational resources. As a result, at the portfolio level we make several abstractions in order to obtain a solution in a timely manner. The model abstraction is based on the investigation of

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the strategic maintenance actions obtained in Chapter 4. In Chapter 4, we found that the strategic maintenance actions for a multi-component product is that we replace every critical part when its deterioration exceeds a threshold. Thus for simplicity, we assume that a product has one and only one critical part and is inspected periodically. Once a product is inspected, the critical part will be replaced and sent to repair. Moreover, we assume that the problem is deterministic where the provider knows with certainty that the product will not fail before L periods after a critical part is installed in the product. To solve the portfolio problem, we develop an integer program formulation, namely a flow formulation, and propose two heuristic algorithms to solve it. The challenge is to find the optimum maintenance schedule to minimize the total cost that includes both maintenance and parts inventory costs.

The rest of the chapter is organized as follows. We describe our problem in detail in Section 7.2. The notation used in the model is described in Section 7.3. In Section 7.4, we develop an innovative flow formulation for the problem. We propose two heuristic algorithms in Section 7.5. A computational study is presented in Section 7.6 and our conclusion are in Section 7.7.

7.2 Problem Description

We consider a portfolio of I units to be managed over a finite planning horizon of T periods. Each unit consists of a critical part that needs to be replaced periodically based on the reliability characteristics of the part. We assume that the parts do not breakdown before L periods but they are highly likely to breakdown after L periods. As a result, parts should be replaced before L periods, after they are installed in a unit. We also assume that it is not economical or acceptable to replace parts before K periods where $K < L$. Therefore, K is the minimum time that the part must be in a unit, while L is the maximum time that the part can spend in a unit. The time between K and L periods is the valid replacement time for a part installed in a unit. The part in a unit is replaced during the maintenance inspection of the unit. Once the part is replaced by a new part, it will go into repair for R periods. After R periods, the part becomes available to be reinstalled in a unit. Repaired parts are stored in an inventory pool until they are installed in a

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unit. Parts can be reused after repair for a maximum of U number of times. After reaching the maximum usage level, U, a part is salvaged for a salvage value S_u. We define the usage status of a part using the numbers 0,1,...,U. State '0' implies that the part is new. A part is in state i after it has been used for i times. A part in state 'U' can no longer be used in a unit and it has to be salvaged. At any given time, a part can be in one of several locations. We use the numbers $l = -2, -1, 0, 1, 2, \ldots, I$ to denote a location of a part. If a part is in use, we use the integers 1,...,I to specify its unit. If a part is in repair or maintenance, its location is 0, (l=0). If a part is used for U times (maximum usage) its location is set to -1 and it can no longer be used. The objective is to minimize the total cost incurred over the entire planning horizon that includes inspection cost, repair cost, part purchase cost, inventory cost and salvage value.

7.2.1 Numerical Examples

The parts required for maintaining equipment, such as, gas turbines and aircraft engines, are very expensive running over a million dollars. Therefore, it is a common practice to use them up to their full life before scheduling inspections. However, we will demonstrate using an example that this is not always the optimal strategy.

Consider a portfolio of 4 units to be maintained during a time horizon of 11 periods. We have the total of 8 parts, and all parts are new. Parts 1-4 are installed in units 1-4, respectively, while parts 5-8 are not yet purchased. The minimum and maximum allowable period a part can be in a unit (K and L) are 2 and 4 periods. A repair period (R) is 1 period, and the maximum usages allowed for a part (U)is 3 times. The part purchased cost C_p is 10,000. The inspection cost C_i and the repair cost C_r is 2000. The inventory cost C_h is 125 per part per period. The salvage value S_u is 6666, 3333 and 0 if a parts is used once, twice and three times, respectively.

Table 7.1 illustrates two maintenance strategies i.e. a "Full Life" strategy and the optimal strategy. The full life strategy is in the column titled "Full Life", while the optimal strategy is presented in the column titled "Optimal". The numbers in the cells represent a part's number, which is installed in the unit number shown in

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the second row. In the full life strategy, parts are utilized up to their full life (L periods). Thus, our schedule is to change parts 1-4 from units 1-4 by parts 5-8 at period 5. Parts 5-8, then, are used in units 1-4 until period 8, while parts 1-4 are in the inventory. At time period 9, parts 1-4 are reinstalled in units 1-4 and used until the end of planning horizon, while parts 5-8 are in the inventory.

For the optimal strategy, we use parts 1-4 in units 1-4 from periods 1-3. At time period 4, units 1 and 3 are scheduled to change parts 1 and 3 by parts 8 and 6, respectively. Parts 1 and 3, then, go to repair for 1 period and are available to be reinstalled in units 2 and 4 in period 5. They stay in units 2 and 4 until period 8. Parts 8 and 6, which are in units 1 and 3 in period 4, are used until period 7, before they are replaced by parts 4 and 2 in period 8. At time period 8, parts 1 and 3 are installed in units 2 and 4 and remain in units 2 and 4 until the end of planning horizon.

Table 7.1: Numerical examples of the maintenance schedule

	Full Life				Optimal			
Time\ Unit	1	2	3	4	1	2	3	4
1	1	2	3	4	1	2	3	4
2	1	2	3	4	1	2	3	4
3	1	2	3	4	**1**	2	**3**	4
4	**1**	**2**	**3**	**4**	8	**2**	6	**4**
5	5	6	7	8	8	1	6	3
6	5	6	7	8	8	1	6	3
7	5	6	7	8	**8**	1	**6**	3
8	**5**	**6**	**7**	**8**	4	**1**	2	**3**
9	1	2	3	4	4	8	2	6
10	1	2	3	4	4	8	2	6
11	1	2	3	4	4	8	2	6
Total cost	59504				58002			

7.3 Notation

We use the following notation in our problem formulation.

T = The number of time periods in the planning horizon.

t = time period index, $t = 1, \ldots, T$.

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I = The number of units in the portfolio.

i = index on units. $i = 1, 2, \dots, I$.

K = Minimum number of time periods that a part needs to be in a unit before it can be replaced.

L = Maximum number of time periods that a part can be in a unit before it should be replaced.

R = The number of time periods needed to repair a part so that it can be re-used.

U = The number of times a part can be used before it needs to be scrapped,

u = index on usage levels, $u = 1, \dots, U$.

To help formulate the problem mathematically, we assume a pool of new parts to draw from during the entire planning horizon. These parts that are yet to be purchased are specified to be at location -2. The number of parts in this pool is greater than the maximum number of new parts needed for the entire planning horizon.

P = Upper bound on the total number of parts required to service all the units over the planning horizon, T.

p = index on parts, $p = 1, \dots, P$;
We assume that parts $p = 1, \dots, I$ are in units $i = 1, \dots, I$. respectively at the start of the time horizon; the parts $p = I + 1, \dots, P$ will be purchased as needed.

l = Location of a part, $l = -2, -1, 0, 1, \dots, I$.

C_p= Purchase cost per part.

C_i= Inspection cost per unit.

C_r= Repair cost per part.

C_h= Holding cost per part per period.

S_u= Part salvage value after u usages.

H_i= Part Life left in unit i at t=0.

In an earlier paper [81], we developed an integer programming formulation for the problem that is described in Appendix C. This is a natural formulation that attempts to assign parts to units by time period. In the next section, we introduce

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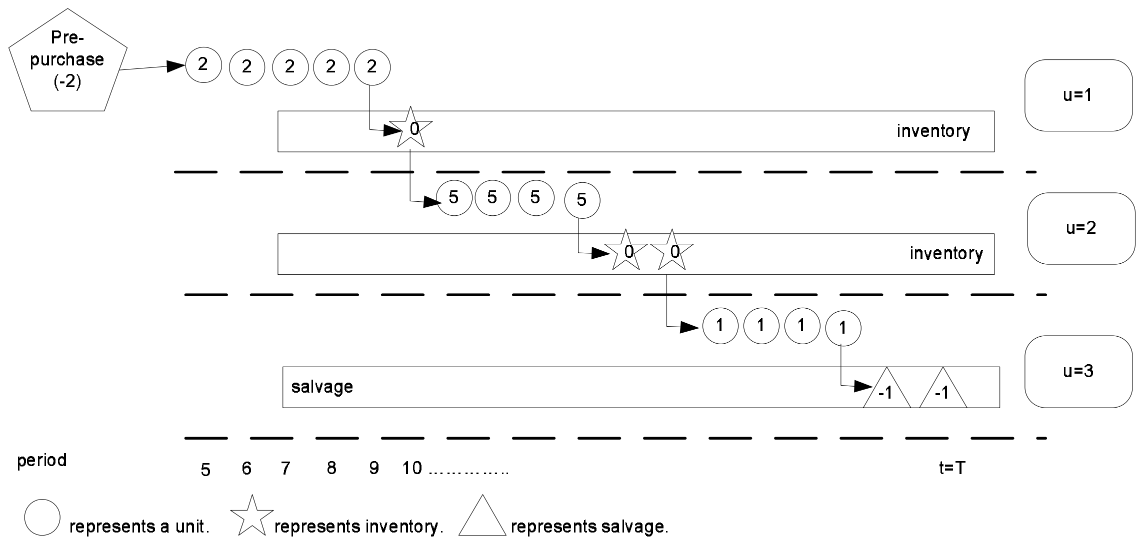

Figure 7.1: The graph represents the concept of Flow Formulation Approach

an innovative formulation, which is much more computationally efficient than the one described in the appendix.

7.4 Flow Formulation

In this section, we develop our innovative flow formulation for the problem when a part flows from one location (unit, inventory, pre-purchased or salvage) to another at the beginning of each period. Figure 7.1 illustrates the flow of a part from pre-purchased state to the fully used (salvage) stage during the course of time. The part is purchased at time period 5 to be placed in unit 2, therefore the part flows from location -2 to location 2 in time period 5. Let $K = 3, L = 5, R = 1$ and $U = 3$ i.e. the part needs to be replaced after spending between 3 and 5 periods in a unit, the time take to refurbish the part is one period and the part can be used at most 3 times. Therefore, unit 2 must be inspected again between time periods 8 and 10. As shown in the figure, unit 2 is inspected at the start of time period 10 and the part flows to location 0 (repair/inventory). Since R=1, the part has to spend a minimum of one period at location 0 before it becomes available to be placed in another unit. In this example the part spends two periods at location 0 (one period in repair and another in inventory). At time period 11, unit 5 is inspected and the

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part under consideration is placed in that unit. Note that the part's usage level is now 2. Prior to time period 11, the usage level of the part was u=1, since it was in its first usage. In time period 15, unit 5 is inspected again and the part flows to location 0 (repair/inventory). It stays at that location for two periods before it is installed in unit 1 at period 17. The usage level of the part is now 3 which is the maximum usage allowed. In period 21, unit 1 is inspected again and the part flows into location -1 (salvage) and stays in there until the end of planning horizon.

The decision variables in our formulation are f_{pijtu} where

f_{pijtu} =1 if part p flows from location i to j at time t with usage level u.
=0 otherwise.

In our example depicted in Figure 7.1, if $p = 7$ is the part under consideration, the values of the variables f_{7ijtu} are as follows. The variables $f_{7,-2,2,5,1}$, $f_{7,2,2,6,1}$, $f_{7,2,2,7,1}$, $f_{7,2,2,8,1}$, $f_{7,2,2,9,1}$, $f_{7,2,0,10,1}$, $f_{7,0,5,11,2}$, $f_{7,5,5,12,2}$, $f_{7,5,5,13,2}$, $f_{7,5,5,14,2}$, $f_{7,5,0,15,2}$, $f_{7,0,0,16,2}$, $f_{7,0,1,17,3}$, $f_{7,1,1,18,3}$, $f_{7,1,1,19,3}$, $f_{7,1,1,20,3}$, $f_{7,1,-1,21,3}$, $f_{7,-1,-1,22,3}$ are all equal to 1 and the rest of the values of f_{7ijtu} are all equal to zero.

The objective function to be minimized which is the total cost incurred over the entire planning horizon is as follows.

$$
\begin{aligned}
C_p \times \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I} f_{p(-2)it(1)} + C_i \times \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{u=1}^{U}(f_{pi(0)tu} + f_{pi(-1)tu}) \\
+C_r \times \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{u=1}^{U} f_{pi(0)tu} + C_h \times \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{u=1}^{U}(\sum_{i=1}^{I} f_{pi(0)t,u} + f_{p(0)(0)tu}) \\
-\sum_{p=1}^{P}\sum_{i=-1}^{I}\sum_{j=-1}^{I}\sum_{u=1}^{U}(S_u \times f_{pijTu})
\end{aligned}
\tag{7.1}
$$

The five terms in the objective function above are the parts purchase cost, the inspection cost, the repair cost, the inventory cost and the salvage value, respectively. The constraints in our formulation are as follows.

System constraints: Constraints 7.2 and 7.3 ensure that at a given time, t, a part

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can be only in one location and a unit can have only one part, respectively.

$$\sum_{u=1}^{U}\sum_{i=-2}^{I}\sum_{j=-2}^{I} f_{pijtu} = 1 \qquad \forall p, t \tag{7.2}$$

$$\sum_{u=1}^{U}\sum_{p=1}^{P}(f_{piitu} + f_{p(0)itu} + f_{p(-2)itu}) = 1 \qquad i = 1, 2, \ldots, I, \forall t \tag{7.3}$$

Valid replacement constraints: Constraint 7.4 ensures that a part spends a minimum of K periods in a unit before it flows out to repair or salvage locations,

$$f_{pii(t+m)u} \geq f_{p(0)itu} + f_{p(-2)itu} \tag{7.4}$$

$$\forall p, u, i = 1 \ldots I, t = 1 \ldots T\text{-}K + 1, m = 1 \ldots K - 1$$

while constraint 7.5 ensures that a part does not spend more than L periods in a unit.

$$\sum_{m=K}^{L}(f_{pi(0)(t+m)u} + f_{pi(-1)(t+m)u}) \geq f_{p(0)itu} + f_{p(-2)itu} \tag{7.5}$$

$$\forall p, u, i = 1 \ldots I, t = 1 \ldots T\text{-}L + 1$$

Repair Constraint: Constraint 7.6 ensures that a part spends a minimum of R periods at location '0' (repair/inventory) before it flows to a unit.

$$f_{p(0)(0)(t+m)u} \geq \sum_{i=1}^{I} f_{pi(0)tu} \tag{7.6}$$

$$\forall p, u, i = 1 \ldots I, t = 1 \ldots T\text{-}R + 1, m = 1 \ldots R - 1$$

Flow balance constraints: A part that flows into a unit at time t continue to be in that unit at time $t + 1$ or flows out to repair ($l = 0$) or salvage ($l = -1$).

$$f_{p(-2)itu} + f_{piitu} + f_{p(0)itu} = f_{pi(0)(t+1)u} + f_{pi(-1)(t+1)u} + f_{pii(t+1)u} \tag{7.7}$$

$$i = 1 \ldots I, \forall p, u, t = 1 \ldots T - 1$$

A part that is in inventory in period t should continue to be in inventory with the same usage level at time $t + 1$ or move into a unit at time $t + 1$ with usage level

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$u + 1$.

$$\sum_{i=1}^{I} f_{pi(0)tu} + f_{p(0)(0)tu} = \sum_{i=1}^{I} f_{p(0)i(t+1)(u+1)} + f_{p(0)(0)(t+1)u} \tag{7.8}$$

$$\forall p, t = 1 \dots T-1, u = 1 \dots U-1$$

An unpurchased part (in location -2) at time t continues to remain at that location or moves into a unit i in time period $t + 1$.

$$f_{p(-2)(-2)t(1)} = \sum_{i=1}^{I} f_{p(-2)i(t+1)(1)} + f_{p(-2)(-2)(t+1)(1)} \tag{7.9}$$

$$\forall p, t = 1 \dots T-1$$

Once a part enters location -1 (salvage) it continues to remain in that location. In other words once a part is expended, it can no longer be used.

$$f_{p(-1)(-1)tU} + \sum_{i=1}^{I} f_{pi(-1)tU} = f_{p(-1)(-1)(t+1)U} \qquad \forall p, t = 1 \dots T-1 \tag{7.10}$$

Initial conditions: These constraints describe the state of the parts that are in stalled at the start of the time horizon.

$$f_{iii(1+m)1} \geq f_{iii(1)(1)} \qquad i = 1 \dots I, m = 1 \dots H_i - (L - K + 1) \tag{7.11}$$

$$\sum_{m=1}^{H_i} (f_{ii(0)(1+m)1} + f_{ii(-1)(1+m)1}) \geq f_{iii(1)(1)} \qquad i = 1 \dots I \tag{7.12}$$

7.5 Heuristic Solutions

Our innovative flow formulation solves a larger problem than our earlier assignment formulation, however, the run time is very large. We therefore develop two heuristic algorithms for the problem. The first heuristic, a myopic heuristic, repeatedly solves a short-horizon integer program and advances until it obtains the solution of the entire planning period. Our second heuristic is an iterative search method, where we systematically search over the feasible region to find a good solution.

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7.5.1 Myopic Heuristic

The myopic heuristic (MH) exploits the fact that we can solve a smaller version of the problem to optimality in a reasonable amount of time. Our strategy, thus, is to suitably solve several short-planning horizon (myopic period) integer programs instead of one long-planning horizon problem. The myopic period (t_m) is the roll-over period for which the smaller versions of the problem are solved. The myopic heuristic has two main procedures. The first procedure is *Initialization*, where we fix the value of f_{pijtu} from the solution for the myopic period to set up the next rolled-over myopic problem. The second procedure is *Solving*, where we solve an integer program of planning period t_m. The algorithm of the myopic heuristic is as follows.

Initialization

Define a myopic period t_m.

Let $t' = t_m$.

Loop

Do until $t' = T$

1. Solve a myopic problem.
2. Initialize roll-over.

   Fix the values of f_{pijtu} from period 1 to t'.
3. Let $t' = t' + t_m$.

End Do loop

7.5.2 Iterative Search Heuristic

The Iterative Search (IS) heuristic iteratively searches through a feasible region to find the best solution. The initial solution for the IS exploits the fact that the "Full Life" strategy is common in practice. Our heuristic then looks to break these ties (several replacements in the same period) of the solution in order to reduce the holding cost per period, and ultimately the total cost. The IS resembles a forward recursion of a dynamic program, where it tries to find a better solution while ensuring

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problem feasibility by advancing parts' replacements (breaking the tie) iteratively from period 1 until T. The algorithm, however, traverses the planning period (1-T) multiple times, defined as a sweep, to identify feasible ties to break.

The heuristic advances a part's replacement if there are at least two parts' replacements (a tie) in the same period. The tie can be broken arbitrarily. In our scheme, we use the lowest part number to be replaced first. At a time, exactly one replacement is advanced by one period. The solution is updated to ensure that problem feasibility is consistent with the advancement. The total cost is calculated, and the minimal total cost observed through the iterations is kept as a benchmark. Every single part advancement implemented is defined as an iteration, since part advancements are accompanied by corresponding modifications that yield a new feasible solution. The algorithm terminates and returns the parts replacement schedule corresponding to the minimal solution observed before reaching the maximum iterations allowed to visit bad solutions (similar to Tabu search) or when there are no ties that can be broken feasibly. The algorithm for the IS heuristic is as follows.

Procedure Iterative Search Heuristic

1 Set *bestSchedule* $\leftarrow$ full life parts replacement schedule

2 Set *bestCost* $\leftarrow$ total cost incurred on full life replacement schedule

3 Set *iterationCount* $\leftarrow$ *maxIterations*

4 Set $t \leftarrow 1$, the second time period in the horizon

    Do while *iterationCount* $\leq$ *maxIterations* and $t < T$

        If *numInspection* > 1 then

            If it is feasible to advance an inspection by one period

                Select an inspection to be advance (if more than one unit's
                    inspection can be advanced, select the unit with
                    the most used part)

                Update the entire schedule

                Let *currentCost* $\leftarrow$ total cost of the updated schedule

                If *currentCost* $<$ *bestCost* then

                    Set *bestSchedule* $\leftarrow$ *currentSchedule*

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Set $bestCost \leftarrow currentCost$

End if

Set $iterationCount \leftarrow iterationCount{+}1$

Set $t \leftarrow 0$

End if

End if

Loop

End *procedure*

Next section will discuss the results and computational time used to solve the problem using both heuristics.

7.6 Computational Study

In this section, we present a computational study that compares the procedures that we presented in the chapter. We used a set of 23 problems that we described in Table 7.2 in our experiments. The problem parameters are in the columns of the table. The inspection and the repair costs are shown under the column titled $C_i{+}C_r$, while the inventory cost is shown in the column titled C_h. The column titled "initial condition" indicates the maximum number of periods that the parts that are currently in the units can continue to remain in them. The last two columns show the number of variables and the constraints, respectively in the flow formulation of the problem. For example, problem 1 is a 4 unit problem over a horizon of 12 time periods. The minimum and maximum time periods that a part can spend in a unit are 2 and 4 respectively. There are 4 new parts in the parts pool and it takes one period to repair a unit. The holding cost is 125 and the cost of inspection and repair is 2000. At time period 1, parts in units are all new.

We implemented the flow formulation and the myopic heuristic in AMPL and solved the problems using CPLEX 9.0 solver on a Pentium 4 machine with 3 GHz processor, and 1 GB memory. We implemented the iterative search heuristic in Visual Basic. Table 7.3 compares the performance of our heuristics with that of solving the integer programming formulation using AMPL & CPLEX. We report the cost incurred using the iterative search heuristic (IS) in the second column of

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Table 7.2: The number of variables and constraints of the test problems

Problem	I	T	P	K	L	R	Ci+Cr	Ch	Initial Condition	# of Variables	# of Constraints
1	4	12	8	2	4	1	2000	125	[4,4,4,4]	14,112	6,949
2	4	12	8	2	4	2	1000	125	[4,4,4,4]	14,112	7,213
3	4	12	8	3	4	1	2000	125	[1,3,4,4]	14,112	7,718
4	4	12	8	3	4	2	2000	125	[4,4,4,4]	14,112	7,721
5	4	24	12	4	6	2	1000	250	[6,6,6,6]	42,336	27,981
6	4	24	12	5	6	2	1000	250	[6,6,6,6]	42,336	30,289
7	5	20	15	3	4	1	2000	250	[4,4,4,4,4]	57,600	35,775
8	4	36	12	6	8	2	2000	125	[8,8,8,8]	63,504	50,933
9	4	36	16	7	8	2	2000	250	[8,8,8,8]	63,504	54,393
10	5	24	15	3	4	1	2000	125	[1,3,3,4,4]	69,120	43,471
11	5	24	15	3	4	1	2000	125	[4,4,4,4,4]	69,120	43,475
12	5	48	25	3	4	1	2000	125	[1,3,3,4,4]	230,400	149,281
13	6	36	30	2	4	1	4000	250	[4,4,4,4,4,4]	262,440	159,983
14	6	36	30	3	4	1	2000	125	[1,2,3,3,4,4]	262,440	177,263
15	5	48	30	5	6	1	2000	250	[6,6,6,6,6]	276,480	215,100
16	4	60	32	7	8	1	1000	125	[8,8,8,8]	282,240	249,009
17	4	84	32	5	6	1	1000	125	[6,6,6,6]	395,136	301,321
18	4	96	36	5	6	1	1000	125	[6,6,6,6]	508,032	389,101
19	5	48	60	3	4	1	1000	250	[4,4,4,4,4]	552,960	357,920
20	5	72	40	4	6	1	2000	125	[6,6,6,6,6]	552,960	438,510
21	6	72	36	7	8	1	1000	250	[8,8,8,8,8,8]	629,856	593,939
22	4	108	40	5	6	1	1000	125	[6,6,6,6]	635,040	488,017
23	4	120	44	5	6	1	1000	125	[6,6,6,6]	776,160	598,069

the Table 7.3. The costs incurred using the other methodologies are reported as a percentage below the IS cost in the composite column titled "% improve". The percentage reported in these columns are computed as $\frac{ISCost-Cost}{ISCost} \times 100$. The run times comparison is presented in the composite column titled "Runtime". Under the myopic heuristic column, the myopic period is reported under column "myopic period".

Overall the problems tested, the myopic heuristic took 35.1 second on an average. On the other hand, the runtime of the AMPL/CPLEX solver with no initial solution was very poor. The IP was unable to find a basis in 4 hours for problems 12 to 23 ($T \geq$ three years). The results of the myopic heuristic match the optimal solution obtained from the IP and are better in many problems, where a solution is returned from IP after four hours.

We ascertain the quality of the myopic heuristic by testing it with solutions obtained from the IP with initial condition. We supply the output from the IS heuristic as the initial condition to the solver. The results are in column "IP After 4 hours with IS Initial solution". After problem 10, the IP solver could not improve

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the result from IS heuristic. Nevertheless, our myopic heuristic gives better objective values around 3%.

Table 7.3: The computational times and the results of the test problems

Problem	IS	Myopic Heuristic				IP After 4 hours			IP After 4 hours with IS Initial Condition		
	Cost	Cost	Runtime	% Improve	myopic period	Cost	Runtime	% Improve	Cost	Runtime	% Improve
1	20000	20000	0.5	0.00	2L	20000	1226.0	0.00	20000	14.9	0.00
2	20000	20000	0.3	0.00	2L	20000	23.0	0.00	20000	10.4	0.00
3	23375	23375	0.5	0.00	L+R+1	23375	17.8	0.00	23375	6.9	0.00
4	20000	20000	0.3	0.00	L+R+1	20000	0.3	0.00	20000	0.1	0.00
5	30000	26000	1.0	13.33	L+R+1	22500	14400.2	25.00	22500	14400.3	25.00
6	36000	30000	2.5	16.67	L+R+1	30000	7883.1	16.67	30000	6235.2	16.67
7	57750	56750	1.6	1.73	L+R+1	55500	14400.1	3.90	57500	14400.8	0.43
8	46000	40500	1.7	11.96	L+R+1	41750	14400.4	9.24	43125	14400.4	6.25
9	60000	58750	13.9	2.08	L+R+1	58750	14400.2	2.08	57500	14399.4	4.17
10	65750	61500	1.5	6.46	L+R+1	68875	14400.2	-4.75	65750	14399.9	0.00
11	70250	62875	1.3	10.50	L+R+1	65625	14400.2	6.58	70250	14400.4	0.00
12	130500	126750	5.6	2.87	L+R+1				130500	14401.0	0.00
13	241250	232000	32.4	3.83	L+R+1				241250	14400.5	0.00
14	115625	115375	114.6	0.22	L+R+2				115625	14400.4	0.00
15	94750	93500	4.5	1.32	L+R+1				94750	14400.1	0.00
16	37625	36250	4.0	3.65	L+R+2				37625	14401.0	0.00
17	66875	66000	18.2	1.31	L+R+2				66875	14400.5	0.00
18	80750	75250	23.5	6.81	L+R+2				80750	14400.4	0.00
19	76750	76000	3.8	0.98	L+R+1				76750	14400.5	0.00
20	135250	131000	403.1	3.14	L+R+2				135250	14401.5	0.00
21	82500	82750	119.4	-0.30	L+R+2				82500	14403.6	0.00
22	84875	85750	25.6	-1.03	L+R+2				84875	14403.6	0.00
23	95875	94250	27.7	1.69	L+R+2				95875	14404.9	0.00

7.7 Conclusions

In this chapter, we study a managing of a portfolio of long-term service agreements to determine the maintenance schedule for the customers' products (units). The MPLTSA problem is a combination of the traditional maintenance schedule problem for the units level, the machine replacement problems for the parts level, and the inventory problem where we want to keep the minimal inventory level. We model the MPLTSA problem as a flow formulation, when a part flows from one unit to another unit in each period. Two heuristics are proposed which are the Iterative Search heuristic and the Myopic heuristic. The Myopic heuristic performs better as shown in Table 7.3.

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CHAPTER 8
Conclusions and Future Works

This dissertation discussed the analysis of the delivery of LTSAs where we created the optimal strategic operations, service delivery and risk management strategy for the provider. In this chapter, we conclude our findings and insights, and suggest some future directions of our research.

8.1 Conclusions

Our study considered two challenging problems faced by the provider of LTSAs, i.e., a strategic operations management problem and a strategic business management problem. The strategic operations management problem considered a long-term maintenance strategy for the products, while the strategic business management problem developed a framework for risk management and assessment for the provider.

The strategic business management problem aimed to find the service delivery strategy which minimized costs and risks. We began the analysis of this problem by identifying potential sources of risks of LTSAs. Risk identification helped the provider completely understand the nature of risks and be able to develop an effective risk mitigation plan for properly managing the risks of the service delivery. We identified nine sources of risks affecting the service delivery in Chapter 3. The sources of risks included product design, product manufacturing and installation, physical service infrastructure, knowledge-based infrastructure, service design or contract setup and specification, financial resource management, sales and marketing, government regulations, and legal issues.

Product design, product manufacturing and installation, physical service infrastructure and knowledge-based infrastructure directly affected the design of the service delivery, since the service design was created based on the interrelation between products and their infrastructure. Financial resource management and sales and marketing could be viewed as endogenous sources of risks, while government

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regulations and legal issues were exogenous sources of risks.

From these nine categories, we could broadly group them into four classes, i.e., product risks, service risks, financial risks, and extreme-event risks. Product risks concerned risks that occurred because of poor product quality. As a result, they included product design and product manufacturing and installation. Service risks took into account risks which happened during the service provisions. They involved contract setup and specification, physical service infrastructure and knowledge-based infrastructure. Financial risks referred to risks of cash flow. Thus sales and marketing and financial resource management directly affected financial risks. Lastly government regulations and legal issues were considered as extreme-event risks because they were unlikely to happen but could largely affect the service process. In order to develop an effective risk management strategy, the provider needed to thoroughly study risks resulted from these sources in order to understand their effects and take advantage of their interrelations.

After identifying sources of risks of LTSAs, we developed a framework determining strategically optimal maintenance actions for a multi-component system when only product risks were considered. For this problem, each component degraded continuously with jumps. The health and the criticality of the components determined the condition of the system. Once the condition of the system reached a certain threshold limit, the provider performed a maintenance action in order to improve the condition of the system and to prevent failures. We solved this problem using an Euler-scheme based continuous simulation to find the deterioration levels of the components and the system. Strategically optimal maintenance actions were found using a search procedure. The results from our sample product suggested that it was better to perform an opportunistic based maintenance when the system needed maintenance. The analysis of product risks setting gave a powerful insight of the maintenance strategy based only on maintenance costs perspective.

Once we understood how product risks affected our maintenance strategy, we developed a quantitative risk management framework to achieve an optimal service operations strategy of the delivery of LTSAs for the provider. The analysis took into account post installation risks or service risks which included product relia-

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bility, maintenance, service infrastructure, contract definitions, and finance. When service risks were incorporated, the optimal maintenance strategy which considered only the aspects of maintenance costs was no longer the winning solution. The provider could not completely ignore the insights of the maintenance strategy which considered only maintenance costs either because the optimal maintenance strategy considering only product risks was constructed from a more detailed analysis where we derived the deterioration of a system and the optimal maintenance action from the evolution of the deteriorations of its components. A search algorithm took advantage of this insight and was developed where we combined a directional search and an evolutionary algorithm together. The optimal strategy obtained moved only little away from the optimal-maintenance-cost strategy and became more aggressive. Yet the optimal strategy reduced the costs of the service and significantly improved the quality of the service.

The dissertation also addressed the investment problem for LTSAs. The objective of the investment problem was to minimize the shortfall risks as well as to achieve maximum profit. In the framework, we adopted a buy and hold strategy where the provider allocated its fixed proportion of wealth to the selected assets for all time. The suggested asset proportion significantly reduced risks of cash flow as well as enhanced the provider's wealth. Moreover it significantly improved the credit rating of the provider. The suggested asset allocation favored bonds, since our objective function was biased toward the shortfall risks and bonds created a guaranteed return to eliminate the shortfall. After applying the suggested mix, the number of shortfall periods and their extent of shortfall were substantially reduced.

In term of the strategic operations management problem, we developed a framework to translate business decisions to operational decisions In particular, we determined when to perform maintenance for a portfolio of LTSAs. The operations management problem of a portfolio of LTSAs was a combination of the traditional maintenance schedule problem for the products level, the machine replacement problem for the components level, and the inventory problem where we wanted to keep the minimal inventory level to support our portfolio. We modeled this problem as a flow formulation where a part flowed from one unit to another unit in each period.

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Two heuristics, which were Myopic heuristic and Iterative Search heuristic, were developed in an attempt to solve the problem efficiently. From the problem sets we solved, the Myopic heuristic outperformed the Iterative Search heuristic.

The dissertation developed a quantitative risk management and assessment framework for the service delivery of LTSAs from the provider's point of view. The study is the first effort to bridge several disciplines, i.e., maintenance management, inventory management, service operations management, and financial and risk management, that affect the service delivery of LTSAs and solve these problems simultaneously. Our framework will find its application in creating the service delivery strategy for the provider of LTSAs as well as the provider of product warranty. Moreover, the framework can find its application in maintenance industry.

8.2 Discussions

The deterioration model and the search algorithm for optimal maintenance actions developed in this paper can be applied to any system for which a strategic maintenance analysis is needed. There are some challenges in a successful application in terms of handling the complexity of the system and calibration of the models. The deterioration model requires developing an appropriate abstraction of the system, since modeling every single component of the real system will result in unmanageable complexity. As a result, as in every model development effort, a decision maker needs to trade off between complexity and accuracy of the model in representing the system. It is critical to decide what level of components or subsystems resolution is kept in a model such that the model is not too complicated, yet good at mimicking the real system.

Once the abstraction is created, the next challenge is to calibrate the model. It is assumed that data in the desirable forms is available for accomplishing this task. This involves transforming the data obtained from system (or component) monitoring devices, such as, measures of temperature, vibration, pressure, crack length, etc., to indicators of health status or deterioration level of the system or components [228]. This transformation will need to take advantage of the detailed data analysis conducted at the engineering design and reliability assessment phase of the system,

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[173, 231, 393]. This is also desirable since data from the monitoring devices in the system operations phase is affected by the current maintenance actions in use. A careful strategy for using a combination of design phase and operations phase data needs to be developed to calibrate the deterioration model (drift, diffusion, and parameters of the jump process), deterioration thresholds, and maintenance recovery and cost models.

Model validation and verification is also very important. The validation and verification of the model reassures the provider that the model created mimics the real behavior of a real system. Thus, results created from the model are meaningful and yield actual benefits in practice. In our study, we are able to qualitatively validate our proposed deterioration model in Appendix A. The deterioration model produces similar behavior with a real system. Quantitative validation of the deterioration models and other models created is also desirable.

The models developed in this dissertation can be further enhanced. For instance, we assumed that the deterioration process of the components are independent of each other, and the interconnection of the components is considered only at the system level. However, it is possible in some cases that the deterioration level of the components is more accurately described as being interconnected with other components, i.e., instead of α_i and β_i, we use α_{ij} and β_{ij}. For example, if parts A and B are neighbors or functionally connected, the deterioration level of component A is affected by the deterioration level of component B and vice versa. As a result, the deterioration level of component A changes when the deterioration level of component B changes, but again the deterioration level of component B also changes since the deterioration level of component A has changed. The drift (α_i) and the diffusion terms (β_i) can also taken to be time-dependent, instead of constants, i.e. $\alpha_i(t)$ and $\beta_i(t)$. These enhancement, however, have a direct bearing on making the model calibration and parameter estimation effort tougher.

The proposed framework offers several benefits to the provider. Most importantly, it allows the provider to design an appropriate service operations strategy that delivers most effective service to its customers. The provider can also benefit from the framework by performing an analysis of trade-offs between different kinds

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of risks. For example, the framework allows the provider to analyze the trade-offs between improving the quality of maintenance and the quality of the monitoring system where the sensitivity analysis which is similar to Section 5.5.1 is performed. The quality of maintenance can be improved through investments to train repair personnel or to purchase better repair equipment, while the quality of monitoring systems can be improved through investments in sensor technology, data transmission system, and control center. The framework also facilitates the analysis of the trade-offs between short-term and long-term strategy. This analysis is attractive if the provider needs to evaluate long-term risks of contracts in a timely manner because solving a very long planning horizon (e.g., more than 20 years) is more computationally expensive than solving a relatively short planning horizon.

8.3 Future Works

In this section, we propose some worthwhile extensions and interesting possible directions of future research. There are several extensions possible for the problems and the developed frameworks discussed earlier. The extensions can be classified into the following problems.

8.3.1 Strategic Business Management

This dissertation completed the analysis of a single LTSA where we found the optimal maintenance and service strategy that reduced both costs and risks as well as the optimal investment strategy which minimized cash flow risks. The framework took five most important sources of risks, i.e., engineering reliability property, maintenance, service infrastructure, and finance, into account. The framework did not consider sales and marketing, government regulations, legal issues, and also future technological changes. These risks impact the costs and the process of the service delivery. The sale and marketing pertains to moral hazard and demand problems, while government regulations impose maintenance constraints and affect how the provider designs its service operations process. The changes in future technology allow the provider to take into account of better technology that can reduce costs, eliminate risks, and improve profits. The framework can be considerably enhanced

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if these risks are incorporated.

The results and insights of our frameworks provide a solid foundation to the analysis of the portfolio, where the portfolio analysis can utilize and take advantage of the optimal service delivery as well as financial management strategies to further get rid of risks which cannot be completely eliminated at an instant level. Thus, the analysis of the portfolio level is required and very essential to the provider. A portfolio of products is an aggregation of several identical physical products, different models of similar physical products, or dissimilar physical products.

Different types of portfolios require different information for the analysis. A portfolio analysis of identical physical products or different models of similar physical products may adopt similar maintenance strategy and face similar risk exposures, while a portfolio of analysis for dissimilar products faces more variety and disparate types of risks and maintenance strategies. These analyses share common goals. The provider aims to hedge risks which cannot be hedged at a single contract level, or, in the context of the analysis of dissimilar products, the provider aims to hedge risks which cannot be hedged at the analysis of a portfolio of similar products. These risks are, for example, financial risks which can be better mitigated at a portfolio level.

Aggregation of several contracts poses new challenges for the provider, since each contract is at a different stage of maturity. Hence, the provider needs to take advantage of interdependence of risks and different information of contracts in order to streamline decisions for each LTSA in the portfolio. Two obvious decisions that the provider needs to make is time of initialization of contracts and the duration of contracts in the portfolio. The main goal of this analysis is to take advantage of different kinds of risks and information of each contract in the portfolio to further reduce risk exposures, since risks of cash flow cannot be totally eliminated even after we employ an optimal financial management strategy as discussed in Chapter 6.

Even though the provider does not have complete freedom in starting contracts, to some extent the provider can negotiate to fasten or delay when contracts can start with its customers. The risks of starting contracts at the same period are obvious, where it is highly likely for the provider to incur large costs at the same

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time due to failures. This may cause the provider not to be able to sustain its cash flows level. Besides the time of initialization of contracts, the provider can evaluate the effectiveness of inventory management strategies which support the service delivery of LTSAs.

Since the provider cannot completely control the time of initialization of contracts, some risks related to timing and duration of contracts cannot be totally eliminated. While costs of providing the service are stochastic, the revenue is mostly deterministic. Therefore, it is still possible that there is a mismatch between costs and revenue. The provider can mitigate the mismanagement of cash flow using the financial framework proposed in Chapter 6. The financial risks can be substantially reduced but may not be totally eliminated. Hence, more sophisticated financial risk management, e.g., asset liability management and hedging strategy where the provider actively adjusts its portfolio, may be developed to address this problem.

Our analysis does not take risks of extreme events into account. The problem can be extended to investigate how extreme-event risks affect the service delivery, operations strategy when extreme events happen, and how to effectively hedge extreme-event risks.

8.3.2 Strategic Operations Management

The strategic business management and the strategic operations management are complement to each other. While the strategic business management imposes guidelines for the strategic operations management, the strategic operations management relays insights from operations to business world.

In the strategic operations management, we transferred decisions at business level to the operational level and achieved the analysis of the optimal part replacement of a portfolio of LTSAs. The problem was formulated as a deterministic integer program, where we assumed that parts could be deterministically replaced between K and L periods. However, parts can be failed before K or after L periods and more importantly parts have their own failure distribution. Formulating the problem as a stochastic program where we incorporate the failure distribution of parts is an interesting and challenging research problem.

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Besides addressing the stochastic version of the problem, adding operational and resource constraints can address more realistic problem. For operational constraints, customers do not want maintenance to be performed during certain time intervals during the year. For example, electricity demands peak in the summer months. Most utility companies would like to operate at full capacity during these months. The model can be modified to avoid scheduling maintenance during high season periods. For resource constraints, the capacities of repair facilities influence the repair time of parts, while the number of maintenance crews available restricts the number of products that can be maintained in a given period. Adding these constraints better mimics the real world problem of LTSA management.

The analysis cannot end here where we decide on which part to be maintained and when to maintain it. The provider also has to decide to which repair facility a removed part will be sent and from which repair facility a unit will get its part. Therefore, the challenge is to find these downstream decisions to be consistent with the part replacement schedule. Moreover, the provider needs to find the strategically cost-effective strategy for repair facilities. The synchronization between maintenance management of a portfolio and the strategic management of repair facilities poses new sets of challenges for the provider, where the provider needs to solve these two problems simultaneously in order to develop the most efficient strategy for the provider. These problems are very interesting and challenging for researchers.

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APPENDIX A
Validating The Deterioration Model With Jumps

In this appendix, we will validate the reliability engineering model (Equation 4.7). The reliability engineering model (or deterioration model) captures the health of a product which is the foundation of the service strategy. As a result, the service delivery strategy and the quality of a solution depend mainly on the reliability engineering model. The solution obtained from the analysis will be misleading and deceitful if the reliability engineering model does not produce similar behavior to a real product. Moreover, it might create a service strategy that is extremely risky as well as highly costly. Among several products on which an LTSA is extended, such as, medical equipments, aircraft engines, locomotives, and gas turbines, we are able to obtain data of a sample gas turbine.

The sample gas turbine consists of six components, i.e., 3 sets of buckets and nozzles. The components are serially connected. The failure time distributions of the components follow a Weibull distribution. The provider adopts a usage based maintenance where the provider repairs the components every 12000 hours and replaces the components every 36000 hours or at failures, whichever occurs first. According to an expert's judgement, these repair and replacement limits correspond to 0.05 and 0.01 probability of failures. Though the components are different, their reliability characteristic and adopted usage based maintenance are similar enough to use the same Weibull distribution. Following these information, we can analytically find the scale and shape parameters of a Weibull distribution of failure times by solving two equations. The scale and shape parameters are 2.637×10^5 and 1.487, respectively.

In our definition, repair means restoring a component/system to a better condition, while replacement means restoring a component/system to its original condition. We capture the effect of maintenance by using a multiplicative model which is similar to Equation 5.9. The threshold levels are set at 55 and 130 for the component and system, respectively. It should be noted that the parameters are carefully

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picked as we do not have hard data to calibrate for the model. As a result, we perform a qualitative validation on the reliability engineering model where we look for similar behavior between the two sets of data.

To see the similarity of the behavior, we attempt to answer three very important questions which compare the behavior of the sample gas turbine and that of our reliability engineering model. The questions are as follows:

1. What is the failure time distribution of the sample gas turbine?
2. Which component causes failures?
3. What does a failure profile look like?

These three fundamental questions are very important because they directly relate to how the provider plan for its maintenance strategy, actions and schedule.

A.1 Failure Time Distribution of a Sample Gas Turbine

We start our validation by checking if the distributions of failure times of the field data and the reliability engineering model are similar to one another. To answer this question, we check if the distributions of failure times of these two data sets are similar to one another for two cases, i.e., with and without maintenance. Validating the failure time distribution is very important because failures are characteristic that the provider most cares for. The provider needs to know the failure distribution in order to plan for its maintenance strategy effectively.

For the distribution of failure times without maintenance of the field data, the distribution of failure times follows Weibull distribution. This is because the shape parameter of its components are the same. The probability plot of Weibull distribution on the left panel also confirms the result as seen in Figure A.1. The scale parameter for the distribution of failure times is found using Distribution Fitting Tool provided in MATLAB v7.04. The parameters for the Weibull distribution are shown in Table A.1.

For the reliability engineering model, we also use Weibull probability plot to check if the distribution of failure times follows Weibull distribution and use

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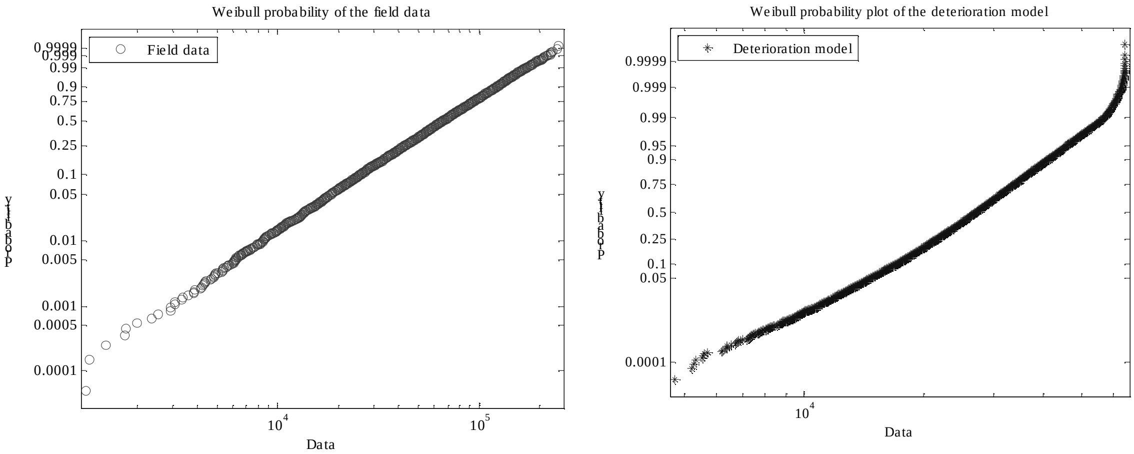

Figure A.1: The Weibull probability plot of the field data (left panel) and the reliability engineering model (right panel)

Distribution Fitting Tool provided in MATLAB v7.04 to find its parameters. The parameters are shown in Table A.1. On the right panel of Figure A.1, we can see that most data are in straight line. Only small number of the data set at the tail does not follow the straight line. We can pictorially conclude that the failure times also follow Weibull distribution. We also confirm if the distribution of failure times follows Weibull by using a hypothesis testing when $\alpha = 0.01$, and the test does not reject the null hypothesis. Thus, we can conclude that the failure times obtained from the reliability engineering model also follow Weibull distribution. Other statistics, e.g., mean and standard deviation, are presented in Table A.1. It should be noted that the mean of failure times of the reliability engineering model is lower than that of the field data. This is because Weibull distribution is a heavy tailed distribution. As a result, there are some very high failure times and, thus, the mean of failure times of the field data is higher due to these outliers.

Table A.1: Parameters of the distribution of failure times when maintenance is excluded

	Field data	Deterioration model
Scale	80748	56440
Shape	1.487	3.17
Mean (hr)	72254	50658
Std (hr)	41919	16316

When maintenance is included in the system, the distributions of failure times

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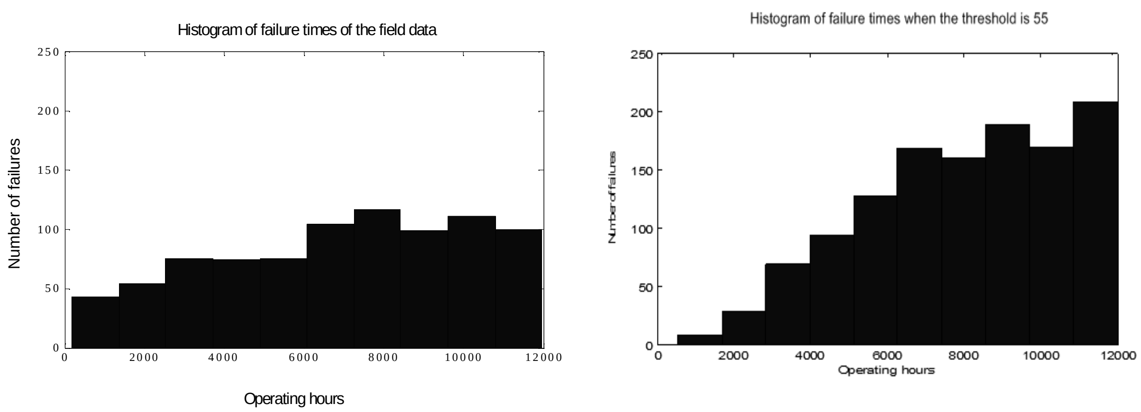

Figure A.2: Histogram of failure times with maintenance of the field data (left panel) and the reliability engineering model (right panel)

are similar to those that exclude maintenance from their system. However, the distributions are truncated at 12000 hours, since the provider repairs its gas turbine every 12000 hours.

To validate the failure time distribution when maintenance is included, we have run the simulation for 10 years with 3000 replications. The distributions of failure times when maintenance is included are shown in Figure A.2.

We can see from Table A.2 that when we set the threshold level to 55, the number of failures of the reliability engineering model are higher than that of the field data. This is because the mean of the failure times of the reliability engineering model is higher.

Table A.2: Parameters of the distribution of failure times when maintenance is excluded

	Field data	Threshold = 55	Threshold = 60
Failures	792	1216	817
Mean (hr)	6458.6	6876.1	7316.1
Std (hr)	3107.1	2297.8	2453.7
Median (hr)	6628	6772	7561

The mean of the reliability engineering model with threshold set at 55 is closed to that of the field data. The difference is less than 400 hours. The mean though is a good statistic. It can be easily affected by outliers. Thus, we also report the median of the failure times in Table A.2. The medians of the failure times of both data sets are very close to each other. We use rank-sum test to check if the medians

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of the two data sets come from the equalled median distributions. The test does not reject the null hypothesis. As a result, we can conclude that the two data sets come from though different distributions but with equal median when we set the threshold at 55.

Failure times are a function of drift and diffusions coefficients, jump terms in the reliability engineering model and thresholds set for maintenance and failures. When we set the failure threshold to be 55, we can see that the two data sets produce similar median and very close mean. However, the reliability engineering model generates higher number of failures. We perform some experiments where we increase the threshold levels of component failure to be 60. As we expected, when we increase the threshold levels, the number of failures is lower, while the mean and the median of failure times are higher as reported in Table A.2. The number of failures when we increase the threshold levels to 60 is now close to that of the field data. We use Z-test to check if the proportion of failures when the threshold increases to 60 is equal to the proportion of failures obtained from the field data. We do not reject the null hypothesis.

A.2 Component Causing Failures

Let consider which component causes failures the most. Because the characteristic and the maintenance policy are similar enough to use the same distribution for the field data and the distributions are independent of each other, the number of failures caused by each component should be uniformly distributed. Figure A.3 shows how failures caused by each component and confirms our hypothesis.

From Figure A.3, we can see that failures caused by each component for the reliability engineering model are also uniformly distributed. We use a Chi goodness of fit test to check if these two data sets come from a uniform distribution. The test does not reject the null hypothesis.

If we analyze Figure A.3 more closely, we can see that components 1 and 6 cause slightly fewer failures than the other components in the reliability engineering model. This is because the reliability engineering model captures the interactions between components, and components 1 and 6 have the least effect. We can con-

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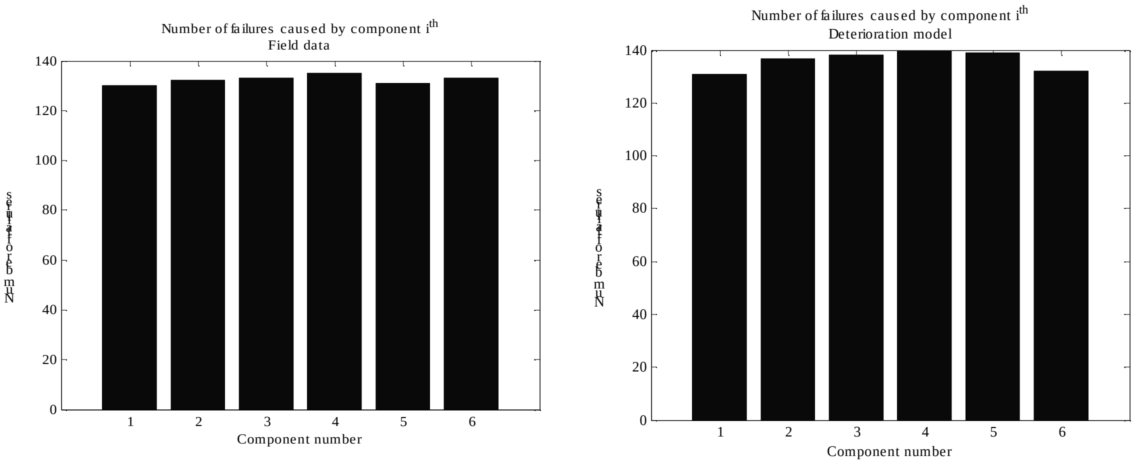

Figure A.3: Histogram of failures caused by each component of the field data (left panel) and the reliability engineering model (right panel)

clude that our reliability engineering produces similar behavior to the field data even though the reliability engineering model captures the interactions between components.

A.3 Failure Profile of a Product

Finally, we consider the failure profile of the product where we consider how many failures occur in each year. The graphs in Figure A.4 present times at which failures occur. As we can see on the right panel, the reliability engineering model needs some time to build up its reliability engineering to cause failures, while the field data does not. For the field data, years 4 and 8 have higher failures compared to other years because there are no maintenance in years 4 and 8 when the provider adopts usage based maintenance. Note that in our simulation the simulation progresses in days, and the periodic maintenance does not fall during years 4 and 8. We use KS-test to check if the proportions of failures in each year of both data sets come from the same distribution with $\alpha = 0.01$. We do not reject the null hypothesis. As a result, we can conclude that the threshold level set for failures each year product similar proportion of failures to the field data.

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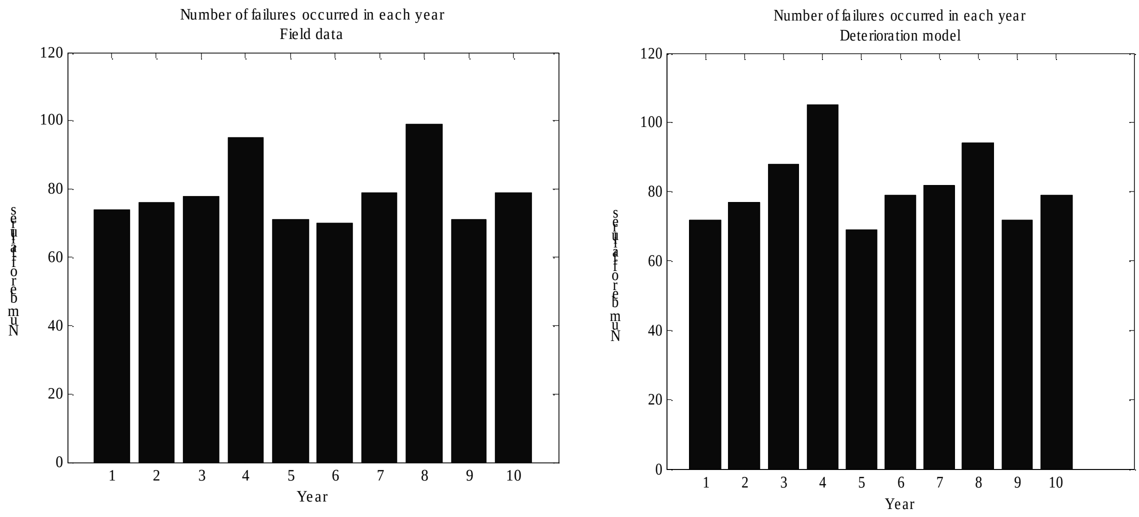

Figure A.4: Histogram of failures occurred in each year of the field data (left panel) and the reliability engineering model (right panel)

A.4 Summary

In summary, we have qualitatively validated the reliability engineering model which is the foundation of the development of the service strategy. Though our aim is to validate every model pertaining to developing service strategy, it is not possible because there is no data to validate for models on the upper level (levels 2-5 in Figure 5.1). In the validation process, we show that the reliability engineering model produces similar behavior to the field data when usage based maintenance is adopted. However, our ultimate goal is to adopt condition based maintenance (CBM) as the main maintenance strategy. If CBM presented in the framework are put in place, we expect that the provider will experience higher number of maintenance and lower number of failures. Since customers have extremely low toleration for failures and penalty fees for failures are very high, the provider will be better off when they adopt CBM as its maintenance strategy.

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APPENDIX B
Mapping the Deterioration of a System From the Deterioration of Its Components

This appendix attempts to create a system model discussed in Chapter 5 which mimics a real system without analyzing and retaining information about components. In Chapter 4, we proposed a model to find the evolution of the deterioration of a system from the deterioration of its components. We will refer to this model as a "component model." The component model provides an insight for the analysis of engineering reliability [161], but it comes at a tremendous computational costs because it requires tracking the evolution of each component's deterioration. Since Chapter 5 focuses on the evaluation of contract properties based on the framework in [162] where risks and appropriate setup of LTSAs outlined in Figure 5.1 are incorporated, applying the component model will be difficult and computationally expensive. Thus, we need a more parsimonious model tracking the deterioration of a system that statistically converges to the deterioration of a system calculated from the component model in each period without having to track each component.

The objective of this appendix is, therefore, to create a more parsimonious model that finds the deterioration of a system without tracking the deterioration of its components, yet the results of the more parsimonious model statistically converge to the results obtained from the component model. To create the more parsimonious model (system model), we need to appropriately fit a parsimonious process to the deterioration process found in Equation 4.7 (the component model). For simplicity, we will refer to the more parsimonious model as a "system model." The appendix will start with a review of the component model proposed in Chapter 4.

In Chapter 4, we proposed a model to find an evolution of the deterioration of a system. The deterioration of a system is a function of the deterioration of its components. The deterioration of a component consists of two parts, a continuous deterioration and a jump deterioration. The continuous deterioration is found by applying a two-stage model to an Ito process, while a jump in deterioration follows

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a Poisson process. The deterioration of component i is derived as follows.

$$\Delta Z_{i,t} = \alpha(Z_{i,t-1}, t)\Delta t + \beta(Z_{i,t-1}, t)\Delta W_{i,t}, \quad \text{(B.1)}$$

$$\Delta C_{i,t} = f_1(Z_{i,t})\Delta t, \quad \text{(B.2)}$$

$$C_{i,t} = C_{i,t-1} + \Delta C_{i,t}, \quad \text{(B.3)}$$

$$J_{i,t} = U_{i,t} \times I_{\{N_i(t^+)-N_i(t^-)=1\}}, \quad \text{(B.4)}$$

$$D_{i,t} = C_{i,t} + J_{i,t}, \quad \text{(B.5)}$$

where $Z_{i,t}$ is an Ito process. The function, $f_1(\bullet)$, can be any positive, integrable function, such as, the exponential function, an absolute value, a square function, etc. $C_{i,t}$ is a continuous deterioration of a component i. $I_{\{N_i(t^+)-N_i(t^-)=1\}}$ is an indicator function indicating a jump of a component i. $N_i(t)$ is the number of jumps of component i up to time t which follows a Poisson process having a rate λ_i. $U_{i,t}$ is the intensity of the jump of component i at time t. It should be noted that the component model is a normative model where we assume that there is no error on measurement of the deterioration of components. The deterioration of a system is, therefore, a function of the deterioration of its components as shown in Equation B.6.

$$D_{sys,t} = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}D_{i,t}D_{j,t}} + J_{sys,t}, \quad \text{(B.6)}$$

where $D_{i,t}$ is the deterioration level of component i. ρ_{ij} is an intensity of connection between components i and j. $J_{sys,t}$ represents the damage caused to a system due to failure of its component(s). $J_{sys,t}$ are defined as follows.

$$J_{sys,t} = \sum_{i=1}^{N} F_{i,t} I_{\{D_{i,t} \geq D_i^{max}\}}, \quad \text{(B.7)}$$

where $F_{i,t}$ represents the degree of damage of the system if component i fails at time t. $I_{\{D_{i,t} \geq D_i^{max}\}}$ is an indicator function indicating failure of component i.

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B.1 Mapping the System Model to the Component Model

In this section, we derive the system model from the component model. We begin this section by expanding the component model.

We rewrite Equation B.6 by substituting Equation B.5 to Equation B.6.

$$\begin{aligned}
D_{sys,t} &= \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}(C_{i,t}+J_{i,t})(C_{j,t}+J_{j,t})+J_{sys,t}}, && \text{(B.8)}\\
&= \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}[C_{i,t}C_{j,t}+C_{j,t}J_{i,t}+C_{i,t}J_{j,t}+J_{i,t}J_{j,t}]+J_{sys,t}}, && \text{(B.9)}\\
&= \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}[C_{i,t}C_{j,t}]+\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}[C_{j,t}J_{i,t}+C_{i,t}J_{j,t}+J_{i,t}J_{j,t}]}\\
&\quad +J_{sys,t}, && \text{(B.10)}
\end{aligned}$$

From Equation B.10, the deterioration of a system depends on four main terms, i.e., (1) the product of the continuous deterioration of components, (2) the product between the continuous deterioration of components and the jump deterioration of components, (3) the product of the jump deterioration of components, and (4) the jump deterioration of the system. Next we will begin our analysis by mapping the continuous deteriorations of components to the continuous deterioration of the system.

B.1.1 Mapping the Continuous Deterioration of the Component Model to the System Model

The continuous deterioration of a system depends on three first three terms in Equation B.10, i.e., (1) the product of the continuous deterioration of components, (2) the product between the continuous deterioration of components and the jump deterioration of components, and (3) the product of the jump deterioration of components. In another word, we can rewrite the continuous deterioration of a system

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as follows.

$$C_{sys,t} = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}[C_{i,t}C_{j,t}] + \sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}[C_{j,t}J_{i,t} + C_{i,t}J_{j,t} + J_{i,t}J_{j,t}]}. \tag{B.11}$$

B.1.1.1 The Analysis of the Product of Component's Continuous Deterioration

In order to map the system model to the component model, the system model should have a similar form to that of the component model. As a result, we propose that the continuous deterioration of a system is captured by a function of an Ito process. Hence, Equations B.12 and B.13 are similar to Equations B.1 and B.2 of the component model, and Equation B.14 gives the continuous deterioration of a system. To map the continuous deterioration of the component model, Equation B.14 must be equal to the first term of Equation B.10, which is $\sum_{ij}\rho_{ij}C_{i,t}C_{j,t}$. As a result, we need to find a function f_2 and a process X_t of Equation B.14 which produce similar system's behaviors to that of the component model. Our plan in this section is as follows. We will first show that f_2 is an exponential function and then show that X_t process is an Ito process.

$$\Delta X_t = a(X_{t-1}, t)\Delta t + b(X_{t-1}, t)\Delta W_t \tag{B.12}$$

$$\Delta S_t = f_2(X_t)\Delta t \tag{B.13}$$

$$S_t = S_{t-1} + f_2(X_t)\Delta t \tag{B.14}$$

According to Chapter 4, the function f_1 is any positive integrable function. Chapter 4 proposed to use f_1 as an exponential function. Thus, we substitute an exponential function (f_1), Equations B.1 and B.2 to Equation B.3, we will obtain

$$C_{i,t} = C_{i,t-1} + e^{(Z_{i,t-1}+\Delta Z_{i,t})}\Delta t. \tag{B.15}$$

Consider only the first term of Equation B.11 after substituting Equation B.15

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to the first term of Equation B.11. We will obtain the followings:

$$C'_{sys,t} = = \sum \rho_{ij} C_{i,t} C_{j,t} \tag{B.16}$$

$$C'_{sys,t} = \sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij}[C_{i,t-1} + e^{(Z_{i,t-1}+\Delta Z_{i,t})}\Delta t][C_{j,t-1} + e^{(Z_{j,t-1}+\Delta Z_{j,t})}\Delta t] \tag{B.17}$$

$$= \sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij}[C_{i,t-1}C_{j,t-1} + (C_{j,t-1}e^{(Z_{i,t-1}+\Delta Z_{i,t})}\Delta t + C_{i,t-1}e^{(Z_{j,t-1}+\Delta Z_{j,t})}\Delta t) + e^{(Z_{i,t-1}+\Delta Z_{i,t})+(Z_{j,t-1}+\Delta Z_{j,t})}\Delta t^2] \tag{B.18}$$

Since Δt is small, Δt^2 approaches to zero. Hence, we can ignore the last term of Equation B.18. Equation B.18 can be written as follows.

$$C'_{sys,t} = \sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij}[C_{i,t-1}C_{j,t-1} + C_{j,t-1}e^{(Z_{i,t-1}+\Delta Z_{i,t})}\Delta t + C_{i,t-1}e^{(Z_{j,t-1}+\Delta Z_{j,t})}\Delta t] \tag{B.19}$$

$$= \sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij}\{C_{i,t-1}C_{j,t-1} + [C_{j,t-1}e^{(Z_{i,t-1}+\Delta Z_{i,t})} + C_{i,t-1}e^{(Z_{j,t-1}+\Delta Z_{j,t})}]\Delta t\} \tag{B.20}$$

According to Equation B.20, the first term of Equation B.20 is $C'_{sys,t-1}$, where $C'_{sys,t}$ process is the pure continuous deterioration process. For the second and the third terms, since we sum over all i and j, Equation B.20 can be reduced to

$$C'_{sys,t} = C'_{sys,t-1} + 2\sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij} C_{i,t-1} e^{(Z_{j,t-1}+\Delta Z_{j,t})}\Delta t \tag{B.21}$$

In order to map the two models, Equation B.14 should be equal to Equation B.21. Therefore, $S_{t-1} = C'_{sys,t-1}$ and $f_2(X_t) = 2\sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij} C_{i,t-1} e^{(Z_{j,t-1}+\Delta Z_{j,t})}$.

Rearrange $\sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij} C_{i,t-1} e^{(Z_{j,t-1}+\Delta Z_{j,t})}$,

we will get $\sum_{i=1}^{N} g_{i,t} e^{\Delta Z_{j,t}}$ where $g_{i,t} = [\sum_{j=1}^{N} 2\rho_{ij} C_{j,t-1}] e^{Z_{i,t-1}}$.

As a result, $f_2(X_t) = \sum_{i=1}^{N} g_{i,t-1} e^{\Delta Z_{i,t}}$.

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At time t, the only unknowns are $\Delta Z_{i,t}$ of every component i. From Equation B.1, $\Delta Z_{i,t}$ is a normal distribution with a mean of $\alpha(Z_{i,t}, t)\Delta t$ and variance of $\beta(Z_{i,t}, t)\Delta W_{i,t}$. Since the processes of $Z_{i,t}$ are driven by independent Wiener processes ($W_{i,t}$), Equation B.19 is a sum of independent lognormal distributions.

The problem of computing the distribution of the sum of independent lognormal random variables has been studied extensively, however, there is no closed form solution to find the sum of independent lognormal random variables. Nevertheless, the numerical convolution of lognormal distributions has shown that a sum of lognormal distributions follows the lognormal law. Hence, a sum of lognormal distributions can be approximated by another lognormal distribution [143]. Beaulieu et al. [54] showed numerically that a sum of finite independent lognormal random variables is approximately lognormal random variables, or mathematically,

$$e^{Y_1} + e^{Y_2} + \ldots + e^{Y_N} \cong e^{Q} \tag{B.22}$$

where Y_i is normally distributed with mean μ_{Y_i} and variance $\sigma^2_{Y_i}$, and Q is a normal random variable.

To apply Equation B.22, f_2 must be an exponential function, and X_t is a Gaussian process. Since X_t is a Gaussian process, ΔX_t is normally distributed with mean $a(X_{t-1}, t)\Delta t$ and variance $b(X_{t-1}, t)\Delta t$. We can find the drift and diffusion terms of the increment of the process X_t by estimating the first and the second moments of the continuous deterioration found from the component model (Equation B.21). However, we cannot exactly match $f_2(X_t) = \sum_{i=1}^{N} g_{i,t-1}e^{\Delta Z_{i,t}}$, since the matching depends on the matching between S_{t-1} and $C_{sys,t-1}$. Therefore, we have a conditional matching as follows.

$$\sum_{i=1}^{N} g_{i,t}e^{Z_{i,t}} = f_2(X_t)|S_{t-1} = C'_{sys,t-1} \tag{B.23}$$

Consider Equation B.23, we cannot estimate the first and the second moments of $\sum_{i=1}^{N} g_{i,t}e^{Z_{i,t}}$ analytically, since $g_{i,t}$ is unknown until a period prior to time t. As a result, we estimate $a(X_t, t)$ and $b(X_t, t)$ numerically.

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To estimate $a(X_t, t)$ and $b(X_t, t)$, we simulated only the continuous deterioration of components and found the deterioration of a system from $C'_{sys,t} = \sum_{ij} C_{i,t}C_{j,t}$. We used the estimation procedure similar to that of estimating the volatility in finance [184]. After obtaining the first two moments of the 1000 replications, we took average of the first two moments (mean and variance) to find $a(X_t, t)$ and $b(X_t, t)$, respectively. We checked the value of $a(X_t, t)$ and $b(X_t, t)$ by performing a KS test of two sets of 1000 replications generated from both the component model ($C'_{sys,t}$) and the system model (S_t). The level of significant was set at 0.01, and the results from KS test were not to reject the null hypothesis. As a result, we concluded that the data generated from the system model (S_t) and from the component model ($C'_{sys,t}$) come from the same distribution.

B.1.1.2 Analysis of the Product of Continuous Deteriorations and Jumps in Deterioration

In a real system, a jump of a component i affects the condition of other components j, thus making the system worsen. We use the product of continuous deteriorations and a jump to capture this effect. The product of continuous deteriorations and a jump, $\sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij}[C_{i,t}J_{j,t} + C_{j,t}J_{i,t}]$, will be positive if and only if a jump of a component occurs. Therefore, we only care for the continuous deterioration of component i at the time a jump occurs. Since we do not retain the deterioration of a component, we propose to use the expectation of the continuous deterioration of a component at time t instead of using the real continuous deterioration of components and model the expectation of a continuous deterioration as a function of time. Taking an expectation to $\sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij}[C_{i,t}J_{j,t} + C_{j,t}J_{i,t}]$, we will have $\sum_{i=1}^{N}\sum_{j=1}^{N} \rho_{ij}[E(C_{i,t})J_{j,t} + E(C_{j,t})J_{i,t}]$. Since the continuous deterioration has an exponential form, we propose that $E(C_{i,t})$ has the following form, $e^{a_i t + b_i}$.

In order to estimate a_i and b_i, we simulated 1000 replications of continuous deterioration of each component and took an average of 1000 replications of the continuous deterioration of each component at every time t. Once we obtained the average of the continuous deterioration at each time step, we took a logarithm of the

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average and estimate a_i and b_i by performing the the least square error technique.

B.1.2 Analysis of the Product of Component's Jump Deterioration

Consider the jump process of a component in Equation B.4. Since the number of jumps follows Poisson process, the jump process of a component is a Poisson process. Now let us consider the term, $\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}J_{i,t}J_{j,t}$. We can write this term as follows

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}J_{i,t}J_{j,t} = \sum_{i=1}^{N}J_{i,t}^2 + \sum_{i=1}^{N}\sum_{i\neq j}\rho_{ij}J_{i,t}J_{j,t} \tag{B.24}$$

Now let us consider the first term of Equation B.24.

$$\begin{aligned} J_{i,t}^2 &= (U_t^i I_{\{(N_i(t)-N_i(t^-)=1)\}})^2 && \text{(B.25)} \\ &= (U_i^t)^2 \times I_{\{(N_i(t)-N_i(t^-)=1)\}} && \text{(B.26)} \end{aligned}$$

From Equation B.26, $I_{\{(N_i(t)-N_i(t^-)=1)\}}$ still follows a Poisson process with mean λ_i.

In order to generate the intensity of a jump, we need to find out which component experiences a jump. Since every jump process of components follows a Poisson process, the combined jump arrival process has a mean of $\sum_{i=1}^{N}\lambda_i$. The probability of component i experiencing a jump is $\frac{\lambda_i}{\sum_{i=1}^{N}\lambda_i}$. Once we can find which component causes a jump, we can generate the intensity of the jump of component i from its underlying distribution.

Now let us consider the term, $\rho_{ij}J_{i,t}J_{j,t}$. The term, $\rho_{ij}J_{i,t}J_{j,t} > 0$ if and only if both components i and j experience a jump at the same time t. In other words, we want to find the probability that the arrivals of two Poisson processes occur at the same time. Mathematically, it is $P(N_i(t) - N_i(t^-) = 1)$ and $P(N_j(t) - N_j(t^-) = 1)$. By the independence of this two events, we can rewrite it as follows.

$P(N_i(t) - N_i(t^-) = 1)$ and $P(N_j(t) - N_j(t^-) = 1)$

$$\begin{aligned} &= P(N_i(t) - N_i(t^-) = 1)P(N_j(t) - N_j(t^-) = 1) && \text{(B.27)} \\ &= (\lambda_i\Delta t)(\lambda_j\Delta t)e^{-(\lambda_i\Delta t+\lambda_j\Delta t)} && \text{(B.28)} \end{aligned}$$

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where $\Delta t = t - t^{-}$. As $\Delta t \longrightarrow 0$, Δt^2 approaches to zero. As a result, we can ignore $\rho_{ij} J_{i,t} J_{j,t}$.

Now we obtained every parameter relevant to find the continuous deterioration of a system ($C_{sys,t}$). We performed a KS test to compare the results from two models. The continuous deterioration of a system calculated from the system model is found by taking a square root from the combination of the three models discussed earlier. We simulated 1000 replications from each model for 10 years and tested a KS test using 0.005 level of significant at every year. The KS test did not reject the null hypothesis. Hence, we can conclude that the two models come from the same distribution at level of significant equal to 0.005.

B.1.3 Mapping the Jump Deterioration Process

Now we will consider a jump of a system. A jump of a system occurs when there exists a component's failure. Mathematically, the jump process of a system is written in Equation B.7. Since $F_{i,t}$ is given, we need to estimate the arrival process of system jumps.

To estimate the parameter of the jump process, we need to estimate the arrival of system jumps. Since the system jump process depends on failures of components, we propose to estimate the arrival process of system jumps numerically. We first simulated the deterioration of each component and observed the interarrival time of critical and non-critical components' failures. Since failure of components are caused mostly by jumps, and component jump follows a Poisson process, the arrival process of system jumps follows a Poisson process.

We performed a KS test to compare the deterioration of a system found from both models. We simulated 1000 replications from each model for 10 years and tested the deterioration every year. The test did not reject the null hypothesis at the significant level of 0.005. Hence, we are confident that the results found from both models come from the same distribution.

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APPENDIX C
Assignment Formulation of the Optimal Part Replacement in a Management of a Portfolio of LTSAs Problem

In this appendix, we present an alternative integer programming formulation of the problem, which we called the assignment formulation. The problem parameters used are the same as those specified in section 7.3, however, we use the following decision variables in the assignment formulation.

x_{ipt} = 1 if part p is in unit i at time t where $i = 0, 1, \ldots, I$
= 0 otherwise.
y_{it} = The part number used by unit i at time t.
a_{pt} = The unit number assigned to part p at time t.
w_{it} = 1 if unit i changes a part at time t.
= 0 otherwise.
f_{pt} = 1 if part p is installed in a new unit
=(a part flows from "Pre-Purchased", "Repair/Inventory" to a unit).
= 0 otherwise.
e_{pt} = 1 if a part changes its location.
= 0 otherwise.
buy_{pt} = 1 if a part p has been purchased at time t.
= 0 otherwise.
$salvage_{pt}$ = 1 if a part p has been salvaged at time t.
= 0 otherwise.
q_{pn} = The number of usage-level a part p has been used in a unit.

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The integer programming formulation is as follows.

Minimize total cost =

$$C_I \times \sum_{i=1}^{I}\sum_{t=2}^{T} w_{it} + C_R \times [\sum_{p=1}^{P}(\sum_{t=1}^{T}(f_{pt}-1)) + [P - \sum_{p=1}^{P}\sum_{t=1}^{T} buy_{pt}]]$$
$$+C_p \times \sum_{p=1}^{P}\sum_{t=1}^{T} buy_{pt} + C_h \times \sum_{p=1}^{P}\sum_{t=1}^{T} x_{0pt} - \sum_{p=1}^{P}\sum_{n=0}^{U} S_n \times q_{pn}$$

Subject to:

$$y_{it} = \sum_{p=1}^{P} p x_{ipt} \qquad i = 1, \ldots, I, \forall t \tag{C.1}$$

$$a_{pt} = \sum_{i=1}^{I} i x_{ipt} \qquad \forall p, t \tag{C.2}$$

$$\sum_{i=0}^{I} x_{ipt} \leq 1 \qquad \forall p, t \tag{C.3}$$

$$\sum_{p=1}^{P} x_{ipt} = 1 \qquad i = 1, \ldots, I, \forall t \tag{C.4}$$

$$y_{i(t-1)} - y_{it} = u_{it} - v_{it} \qquad i = 1, \ldots, I, t = 2, \ldots, T \tag{C.5}$$

$$u_{it} \leq M z_{it} \qquad i = 1, \ldots, I, t = 2, \ldots, T \tag{C.6}$$

$$v_{it} \leq M(1 - z_{it}) \qquad i = 1, \ldots, I, t = 2, \ldots, T \tag{C.7}$$

$$u_{it} + v_{it} \leq M w_{it} \qquad i = 1, \ldots, I, t = 2, \ldots, T \tag{C.8}$$

$$u_{it} + v_{it} \geq M(w_{it} - 1) + \delta \qquad i = 1, \ldots, I, t = 2, \ldots, T \tag{C.9}$$

$$w_{i1} = 1 \qquad i = 1, \ldots, I \tag{C.10}$$

$$a_{p(t-1)} - a_{pt} = b_{pt} - c_{pt} \qquad \forall p, t = 2, \ldots, T \tag{C.11}$$

$$b_{pt} \leq M d_{pt} \qquad \forall p, t = 2, \ldots, T \tag{C.12}$$

$$c_{pt} \leq M(1 - d_{pt}) \qquad \forall p, t = 2, \ldots, T \tag{C.13}$$

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$$b_{pt} + c_{pt} \leq M e_{it} \qquad \forall p, t = 2, \ldots, T \tag{C.14}$$

$$b_{pt} + c_{pt} \geq M(e_{it} - 1) + \delta \qquad \forall p, t = 2, \ldots, T \tag{C.15}$$

$$f_{pt} \leq e_{pt} \qquad \forall p, t = 2, \ldots, T \tag{C.16}$$

$$f_{pt} \geq e_{pt} - x_{0pt} - salvage_{pt} \qquad \forall p, t = 2, \ldots, T \tag{C.17}$$

$$f_{p1} = \sum_{i=1}^{I} x_{ip1} \qquad \forall p \tag{C.18}$$

$$\sum_{j=t}^{t+K-1} w_{ij} \leq 1 \qquad i = 1, \ldots, I, t = 1, \ldots (T - K + 1) \tag{C.19}$$

$$\sum_{j=t}^{t+L-1} w_{ij} \geq 1 \qquad i = 1, \ldots, I, t = 1, \ldots (T - L + 1) \tag{C.20}$$

$$\sum_{t=1}^{T} f_{pt} \leq U \qquad \forall p \tag{C.21}$$

$$\sum_{j=t}^{T-R+1} f_{pj} \leq 1 \qquad \forall p, t = 1, \ldots, (T - R + 1) \tag{C.22}$$

$$\sum_{t=1}^{T} f_{pt} = \sum_{n=0}^{U} nq_{pn} \qquad \forall p \tag{C.23}$$

$$\sum_{n=0}^{U} nq_{pn} = 1 \qquad \forall p \tag{C.24}$$

$$x_{0p1} = 0 \qquad \forall p \tag{C.25}$$

$$x_{ipt} + \sum_{j=1_{j \neq i}}^{I} x_{jp(t+1)} \leq 1 \qquad i = 1, \ldots, I, \forall p, t = 1, \ldots, (T - 1) \tag{C.26}$$

$$\sum_{i=0}^{I} x_{ipt} - \sum x_{ip(t-1)} = buy_{pt} - salvage_{pt} \qquad \forall p, t \tag{C.27}$$

$$buy_{pt} \leq M l_{pt} \qquad \forall p, t \tag{C.28}$$

$$salvage_{pt} \leq M(1 - l_{pt}) \qquad \forall p, t \tag{C.29}$$

$$x_{ip0} = 0 \qquad \forall i, p \tag{C.30}$$

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$$salvage_{pt} - \sum_{j=1}^{t-1} buy_{pj} \leq 0 \qquad \forall p, t \tag{C.31}$$

$$U - \sum_{j=1}^{t} (e_{pt} + f_{pt}) \leq M(1 - salvage_{pt}) \qquad \forall p, t \tag{C.32}$$

$$\sum_{j=1}^{t} (e_{pt} + f_{pt}) - U \geq M(salvage_{pt} - 1) \qquad \forall p, t \tag{C.33}$$

$$buy_{p0} = 0 \qquad \forall p \tag{C.34}$$

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