RELIABILITY, ROBUSTNESS, AND RESILIENCE OF COMPLEX SUPPLY CHAIN SYSTEMS: DESIGN OPTIMIZATION AND ANALYSIS UNDER UNCERTAINTY

A Dissertation by

Abdulaziz Turki Almaktoom

Master of Engineering Technology, Pittsburg State University, 2010

Bachelor of Engineering Technology, Riyadh College of Technology, 2007

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Wichita State University
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The following faculty members have examined the final copy of this dissertation for form and content, and recommend that it be accepted in partial fulfillment of the requirement for the degree of Doctor of Philosophy with a major in Industrial and Manufacturing Engineering.

_____
Krishna K. Krishnan, Committee Chair

_____
Pingfeng Wang, Committee Co-Chair

_____
Ehsan Salari, Committee Member

_____
Hamid M. Lankarani, Committee Member

_____
Ramazan Asmatulu, Committee Member

Accepted for the College of Engineering

_____
Royce Bowden, Dean

Accepted for the Graduate School

_____
Abu Masud, Interim Dean

DEDICATION

To my parents, wife, son, daughter, sisters, and brothers
for their infinite love and support

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ABSTRACT

Despite numerous studies that consider service level, reliability, robustness, and resilience rates of individual factories in a supply chain system (SCS), the interactions among connected factories and the impact of those interactions on overall supply chain reliability, robustness, and resilience have been rarely studied. Moreover, ensuring the reliability, robustness, and resilience while considering uncertainties induced by various sources, such as transportation delay and manufacturing process variability, in individual factories and routes is a highly complex task. An extensive review of the current literature on global SCS design and analysis shows an urgent need to understand the concept of factory-to-factory supply chain systems, and to develop methods and techniques to efficiently measure and design them. Thus, this research addresses different imperative needs for SCSs, which have been structured into six research thrusts: (1) measurement of SCS service level (SL), (2) assurance of system SL robustness in complex supply chain networks (SCNs), (3) cost-efficient robust global SCS design under uncertainty, (4) measurement and optimization of reliability in complex SCSs, (5) measurement of resilience of multi-level SCSs, and (6) measurement and analysis of reliability, resiliency, and robustness of SCSs.

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LIST OF ABBREVIATIONS/NOMENCLATURE

C	Customer
CT	Cycle Time
CT^T	Target Cycle Time
CSL	Cycle-Service-Level
F	Factory
GERT	Graphical Evaluation and Review Technique
GSM	Guaranteed Service Model
hr	Hour
hr/batch	Hours per Batch
M	Manufacturer
MCS	Monte Carlo Simulation
OEM	Original Equipment Manufacturer
P	Demand
RDO	Robust Design Optimization
R	Route
S	Supplier
SC	Supply Chain
SL	Service Level
SCN	Supply Chain Network
SCS	Supply Chain System
TCT	Total Cycle Time

LIST OF ABBREVIATIONS/NOMENCLATURE (continued)

TCT^T	Target Total Cycle Time
VRP	Vehicle Routing Problem
VaR	Value at Risk
Z	Product type

LIST OF SYMBOLS

i	Entity number
j	Entity level number
X	Entity type
k	Factory i in previous level j-1
T^T	Due time
t	Dynamic time point
x_s	sth design variable
ω	Weights attached as per decision-maker preference
$TCT_{ij}(x_s)$	Total cycle time function for service level measure
$\sigma^2_{TCTi,\,j(xs)}$	Variance of total cycle time function for service level measure
$\mu_{TCTi,\,j(xs)}$	Mean of total cycle time function for service level measure
$M_{ij}(x_s)$	Factory service level rate function for service level measure
$\zeta_{i,j}$	Delay function for service level measure
$Q_{i,\,j}$	Target service level rate for service level measure
$SL_{i,j}$	Service level rate
TCT^T	Target total cycle time for service level measure
$CT^T_{i,j}$	Target cycle time at an entity for service level measure
$DT_{i,j}$	Function of cumulative delay due to unbalanced entities for service level measure
SSL	Overall system quality service level rate
$C\mu_{i,\,j}$	Cost function for maintaining processing and transportation service level of ith entity on level j for service level measure
$C\sigma_{i,\,j}$	Cost function for reducing delay and uncertainty to improve service level

LIST OF SYMBOLS (continued)

$\mu\Psi^{L}_{i}$	Lower allowable processing CT time reduction
$\mu\Psi^{U}_{i,j}$	Upper allowable processing CT time reduction
$\sigma\Psi^{L}_{i,j}$	Lower allowable processing CT variation reduction
$\sigma\Psi^{U}_{i,j}$	Upper allowable processing CT variation reduction for service level measure
$\mu\zeta^{L}_{i,j}$	Lower allowable transporting CT time reduction for service level measure
$\mu\zeta^{U}_{i,j}$	Upper allowable transporting CT time reduction for service level measure
$\sigma\zeta^{L}_{i,j}$	Lower allowable transporting CT variation reduction for service level measure
$\sigma\zeta^{U}_{i,j}$	Upper allowable transporting CT variation reduction for service level measure
Ω	Reliability rate
$\sigma_{i,j}$	Standard deviations of entities distribution functions
$\varepsilon_{i,j}$	Delay due waiting time that entity *i* in level *j* spent waiting for products from previous entity *i* at level *j-1*
$\mu_{i,j}$	Mean time of entities distribution functions
$\sigma^2_{i,j}$	Variance of total cycle time function of *i*th entity on level j
Ω^{T}	Target reliability rate
φ	Resilience rate
ψ	Robustness rate
$D_{i,j}$	Recovery duration time
θ	External delay

CHAPTER 1

INTRODUCTION

1.1 Research Motivation and Background

The development of global manufacturing facilities has increased the need for efficient reliable, resilient, and robust supply chain (SC) systems (SCSs). The motivation for this research comes from various factors, one being the tremendous benefit of outsourcing and globalization, which is expected to increase in the next few years and is reflected by international trade, which will exceed $17 trillion by 2020 (Meixell & Gargeya, 2005). One of the advantages of outsourcing is that it can reduce costs in the immediate financial period (Harland et al., 2005). Another factor is the huge financial consequences of mismanaging supply chain systems because of outsourcing and globalization, which increases SCS disruption and risk. For example, the Boeing aircraft company lost $2.6 billion in 1997 because of inefficiencies in their SCS, which led to a shortage of raw materials (Kalakota & Robinson, 1999). On the other hand, having an effective supply chain strategy, the grocery industry could save $30 billion (Kotzab, 1999). Another factor motivating this research is the long production cycle time, where, for example, a box of cereal takes around 104 days getting from the factory into stores (Hussain, 2002).

Several important parameters and approaches considered important in improving SCS efficiency have been used in its quantification, including cost of delivery, ability to meet due dates, and damage during shipping. Studies to develop the most efficient distribution network for an SCS have also been reported in the literature (Cook & Rich, 1999; Kohl & Madsen, 1997; Larsen, 1999; Miller et al., 1960). These studies primarily focus on minimizing distance and identifying the best distribution routes. Bräysy and Gendreau (2005) developed a meta-heuristic algorithm to solve the vehicle routing problem (VRP) with time windows, which aims to identify the least-costly

routes from one depot to others. Chabrier (2006) proposed a solution strategy for the VRP with elementary shortest-path-based column generations to find a set of routes that cover all nodes with minimum traveling distances. The literature on supply chains has also focused on effectively dealing with nature disasters such as tsunamis and earthquakes (Peng et al., 2011; Shukla et al., 2011; Snyder et al., 2006). Mixed-integer nonlinear programming has been formulated based on risk disruption caused by natural disasters, machine breakdowns, terrorism, and wars at facilities in order to maximize total profit (Jabbarzadeh et al., 2012). A value-at-risk (VaR) model has also been developed to measure the risk of SC disruptions caused by natural disaster events (Ravindran et al., 2010). Due to the inherent characteristics, these natural disaster events rarely happen, and hence their cost implication can hardly be fully understood. In an SC structure, most reported studies have focused on a single factory or production system that supplies products to multiple retailers. The upstream SC in which several manufacturers, either in parallel or in series, supply to a final manufacturer poses a different set of constraints and issues. A typical upstream manufacturing supply chain system is shown in Figure 1.1, where M_6 represents the final manufacturer, and M_1, M_2, M_3, M_4, and M_5 represent manufacturers that supply parts to M_6.

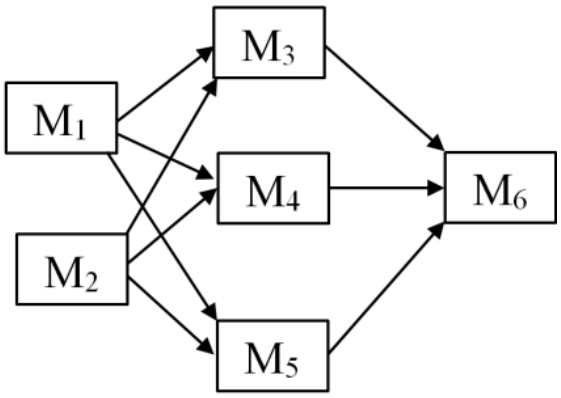

Figure 1.1. Typical upstream manufacturing supply chain system

In the route determination problem, the performance of one route can be determined by performance parameters such as cost of distribution and distance traveled. For upstream supply

chains, important performance parameters include service level (SL), reliability, resilience, and robustness between suppliers, on-time delivery, as well as robustness of the SC that is subject to uncertainties. Wen-sheng and Li (2007) developed a lead-time-contingent pricing model that illustrates how product price is sensitive to delivery time. Results of their study showed that product cost decreases when scheduled delivery time increases, indicating that it is vital to keep the availability of products on time. Azad and Davoudpour (2010) compared a Tabu search algorithm and simulated annealing for minimizing total expected costs while considering the fixed cost to open distribution centers, transportation cost from distribution centers to customers, and expected cost due to disruption situations. However, in their research, they considered disruptions in location and capacity while opening new distribution centers, but they did not consider the cause of disruption and how the impact of disruption can be minimized. Liu and Peng (2009) introduced a reliability index to supply chain systems in order to select suppliers based on the reliability information of candidate suppliers.

1.2 Research Scope and Objectives

The objective of this research was to develop generic methods in order to assist and assess complex supply chain system design and analysis considering different types of uncertainty factors. To achieve this objective, nine key research questions were addressed: (1) How do you measure the performance of the whole SCS consisting of multiple types of entities (factories and routes)? (2) How do you measure the performance of different types of factories that produce different products with different quantities using a single unique measure? (3) How do you design an SCS that satisfies system requirements and minimizes the impact of uncertainty? (4) What is the optimal value for the performance requirement of each entity in the system to satisfy overall SCS requirements? (5) How do you design a cost-efficient SCS, identify an entity in the system to

be improved, and determine the cost of improvement? (6) How do you measure SCS reliability and design it to satisfy reliability requirements? (7) How do you measure and analyze the resilience of complex SCSs? (8) How do you measure and analyze the robustness of complex SCSs? (9) How should decision makers act to implement performance measures and enhance overall system performance? Research solutions to answer these questions have been provided in five main chapters in this dissertation.

Chapter 3: Measurement of Supply Chain System Service Level. This chapter addresses research questions one and two, and proposes an efficient measure that can measure an upstream supply chain system. To assess the performance measurements and analysis of an SCS, a new performance measure, referred to as the service level rate of an SCS, is developed. Measuring service levels is essential for maintaining customer satisfaction. The effective design of a supply chain can be achieved by designing a quantitative service measurement system, and an SL analysis must be incorporated at all levels of the SCS. To validate the proposed SL rate of an SCS, two strategies are attempted: (1) balancing the SCS, and (2) increasing the due dates. In this way, the variability of entities in an SCS can be analyzed. Also, comparisons of target performances and actual performances are possible. By using an appropriate measure, the overall SCS performance can be monitored closely. Successive improvements can be applied to each entity in the SC to determine the impact of improvement on the overall SCS.

Chapter 4: Assurance of System Service Level Robustness in Complex Supply Chain Networks. This chapter addresses research questions three and four. The main ideology of this thrust is to ensure continuous service quality and manage improvement through a logistical and mathematical model optimization such as robust design optimization. Ensuring performance robustness in terms of availability of raw materials and products is of vital importance for SC

management. Thus, it is important to study the effect of uncertainty introduced by factory SL rates on the robustness of overall supply chain network (SCN) performance and present a novel robust design optimization methodology to derive designs of factory SL rates in order to satisfy the SL rate requirement of the system and ensure its robustness. This study employs robust design optimization technique for optimal SL rate design of an upstream supply chain system to guarantee overall system SL rate and ensure its robustness.

Chapter 5: Effect of Cost-Efficient Robust Global Supply Chain System on Service Level Satisfaction. This chapter addresses research question five and emphasizes the results of an efficient global SCS that is focused on the identification of the degree to which dimensions related to logistic service quality influence the overall service level rate while minimizing the quality cost. This research develops a generic robust design optimization model that can be used to determine an entity's value (routes and factories) in a complex SCS that should be improved in order to achieve a required SL rate and reduce the total quality cost. This method will help to redesign an upstream SCS in which the system can be optimized to ensure SL rates, which will lead to improved logistics and reduced costs.

Chapter 6: Measurement and Optimization of Reliability in Complex Supply Chain Systems. This chapter addresses research question six and introduces a novel measure to quantify the reliability of the overall SCS and the reliability of each of its members. It also introduces an optimization approach to design a reliable entity in the SCS such that the reliability rate requirement of the overall SCS is ensured. The need exists for research and methodology that can not only assess the efficiency of a SCS configuration but also provide an efficiently designed SCS configuration with an efficient on-time solution in order to overcome the impact of risks and uncertainties with proven superior performance.

Chapter 7: Measurement of Resilience in Multi-Level Supply Chain Systems. This chapter addresses research question seven which is the need for models and methods for measuring the resilience of a complex SCS. It is important for companies to design supply chains that are resilient. When SCs are impacted by disruptions, they must be designed to allow corrective action that restores their performance to pre-disruption levels. Also, this thrust has defined the concept of resilience and how it can be integrated into the field of complex SCSs.

Chapter 8: Measurement and Analysis of Reliability, Resiliency, and Robustness in Complex Supply Chain Systems. This chapter addresses research questions eight and nine, which involve the development of models and methods for measuring the robustness of an SCS, which is important in order for companies to remain competitive. Also, this chapter provides approaches to improving the reliability, resilience, and robustness of SCSs. A method for implementing these measures is detailed in this chapter.

1.3 Dissertation Overview

The remainder of this dissertation is organized as follows: Chapter 2 reviews the current state-of-the-art design optimization and analysis approaches related to reliability, robustness, and resilience of complex supply chain systems. Chapter 3 presents the developed approach to calculate the service level rate of any given SCS. Chapter 4 presents a proposed robust service level rate assurance design optimization. Chapter 5 presents a cost-efficient robust global SC service level rate. Chapter 6 introduces a reliability rate measure to evaluate system reliability and the optimization model. Chapter 7 introduces a novel resilience measure for evaluating SC resilience. The developed robustness measure is explored in Chapter 8. Finally, Chapter 9 summarizes this dissertation and discusses future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Related state-of-the-art methods of proposed problems within the thrusts of this dissertation are investigated in the following sections of this chapter: Section 2.2 discusses uncertainty and risk factors in the supply chain system. Section 2.3 concerns global SC uncertainty. Section 2.4 presents logistics and the cost of a global SCS. Section 2.5 provides a quantitative SCS performance measure. Finally, Section 2.6 reviews the robust design optimization models and approaches.

2.2 Uncertainty and Risk Factors of Supply Chain Systems

Outsourcing and globalization of supply chains increase business risks (Barry, 2004; Christopher et al., 2011; Waters, 2011), due to the fact that the future operation, process, conditions, and activities of a SCS are largely unknown (Klibi et al., 2010). For instance, numerous SCS risks have been identified in the literature (Christopher & Peck, 2004; Kleindorfer & Saad, 2005; Tang, 2006; Wagner & Bode, 2006). Generally, risks in the SC can be divided into low-level risks and high-level risks. Low-level risks have a high probability of occurrence but low impact. However, these risks can be costly if not managed correctly and swiftly. Examples of low-level risks include quality-control failures, component defects, machine breakdowns, low service levels, high holding costs, high operation costs, market oversupplies, production delays, transportation delays of raw material and finished goods, etc. High-level risks have a low probability of occurrence but a high impact and cost, which are generally difficult to plan for in the future. Examples of high-level risks are workforce strikes, security discrepancies, and physical disasters such as earthquakes, hurricanes, fires, and storms. It is necessary for industries, suppliers, and customers within an SCS to cooperate in order to reduce processing delays and complicated

SC risks (Bowersox et al., 1999; Flynn, et al., 2010; Frohlich & Westbrook, 2001; Zhao et al., 2008). Several studies have been aimed at reducing SC risks. For instance, the work of Zhao-wen et al. (2011) proposed a mixed-strategy game model and a graphical evaluation and review technique (GERT) network to analyze the impact of delay across the entire SC. This was intended to help manufacturers make alternate production arrangements in order to minimize potential losses such as stopping production or giving priority to other products. Sahnoun et al. (2012) presented a simulator to evaluate the work-at-risk, with the objective of reducing delays in production and associated impacts on a supply chain system. This simulator helps to optimally allocate quality inspection points in order to reduce production delays. Zhao et al. (2013) also conducted a study on the risks of SC integration and company performance in a global context based on the performance of manufacturing relationships.

Despite considerable research in the literature on SC risks, studies have rarely reported on the risk associated with an SC system in which factories supply to each other interactively. Existing SCS research has focused mainly on the architecture of one supplier with multiple routes and depots. However, in reality, an SCS could be much more complex, as shown in Figure 2.1. In the case of an upstream SC, multiple supplier factories supply parts to an original equipment manufacturer (OEM), whereby the SCS could consist of a series of factories, each with its definition of variability and risk. Figure 2.1 shows a typical complex SCS, where $M_{i,j}$ presents factory i in level j, C denotes customers, and I, J, and n are total number of factories, levels, and customers, respectively.

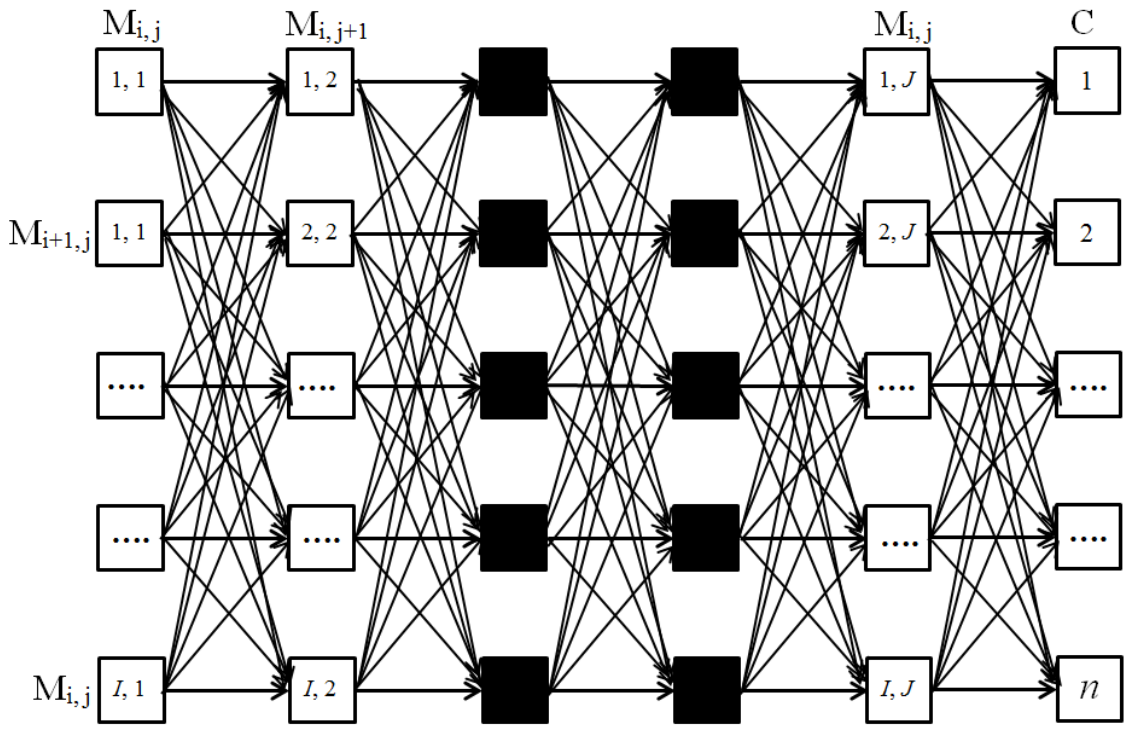

Figure 2.1. Complex supply chain system

2.3 Uncertainty of Global Supply Chain Systems

This section reviews the important issues in a global supply chain. Global supply chain uncertainty causes huge disadvantages, such as increasing risk during transportation, manufacturing, or product designing. In order to maintain an ideal SC, global SC arguments that would assist in research objectives have been reviewed. Research views the global SC as one way to obtain a high-quality product at a low cost. Also, the global SC has a high impact on the entire SC due to its ambiguity and high uncertainty. Therefore, any developed model should be accurate and sensitive to building an efficient global SC. Lack of a better understanding of global SC uncertainty and risk leads to many problems in the current competitive market, with many challenges that sustain the benefit of a global SC.

According to the literature, outsourcing and globalization are expected to increase in the next few years (Meixell & Gargeya, 2005). Harland et al. (2005) has stated that "Outsourcing can

free up assets and reduce costs in the immediate financial period." For example, Coloplast (a Danish healthcare product manufacturer), after a decade of outsourcing a majority of its product parts to Tatabanya in Hungary, reduced labor and production costs (Bals et al., 2013). Companies today not only use outsourcing to reduce labor and production costs, but also for to improve quality, performance, and knowledge by accessing overseas skilled employees.

Today, global supply chain systems are a concern because of their complexity, uncertainty, sensitivity, and cost. The expansion of outsourcing and globalization increases SCS disruption and risk (Barry, 2004; Christopher et al., 2011; Waters, 2011). This includes increased probability of risk, uncertainty in job schedules, and quality dilemmas. Also, many global factors impact the supply chain system. For example, currency fluctuations, economical changes, political situations, lead times, the environment, and uncertainty (Khan & Burnes, 2007; Manuj & Mentzer, 2008; Rao & Goldsby, 2009) all affect SC economics. A large geographical distance increases not only transportation cost but also SC complexity. Also, different cultures, languages, practices, worker skills, equipment, and technology diminish the efficiency of the SCS. Simangunsong et al. (2012) reviewed the supply-chain literature and identified 14 different sources of uncertainty in the SC. They categorized these sources of uncertainty into three types: (1) internal organization uncertainty, which includes organization behavioral issues, product characteristics, control, manufacturing process, decision complexity, and information systems; (2) internal supply-chain uncertainty, which includes end-customer demand, order forecast horizon, supplier, demand amplification, and chain configuration including infrastructure, location, and facilities; and (3) external uncertainties, including disasters (i.e., hurricanes, tornados, fires, earthquakes) and market atmosphere (i.e., competitor behavior, macroeconomic issues, government regulation, currency, and economic changes). One of the key contributions in this research is the development of an

optimization method that helps to identify the entity (factory or route) that should be improved in order to satisfy the overall SCS service level rate with the lowest cost possible while considering uncertainty.

2.4 Logistics and Cost of Global Supply Chain System

Brutal competition in today's global supply chain in meeting customer requirements and maintaining cost have forced companies to concentrate and review their SC logistics. In a typical SC, raw materials and products are produced at one or more factories, then shipped to inventory locations for intermediate storage, and finally shipped to retailers. To minimize cost and improve service, reliability, resilience, and robustness, effective SC strategies must take into account exchanges at various levels in this chain. Therefore, there is a need for better understanding the global SC, which in turn will lead to minimized system-wide cost while satisfying service, reliability, resilience, and robustness requirements. The research in this dissertation emphasizes the results of an efficient global SC that is focused on the identification of the degree to which the dimensions related to service, reliability, resilience, and robustness influence the overall performance while minimizing related cost. In general, in order to maintain a competitive advantage in the context of aggressive competition on the global supply chain, the integration of the supplying strategy in the supply chain system and reinforcement of the role played by logistics in monitoring and controlling the system service level, reliability rate, resilience rate, and robustness rate is important and needed. Accordingly, achieving efficiency and cost effectiveness across the entire supply chain system is possible.

The concept of quality and a global supply chain has significantly changed the business practice of logistics. This began in the mid-nineties as logistics research began to analyze the capacity of logistics to transport quality and thus provide greater service-level satisfaction and

reliability (Mentzer et al., 2004). In fact, many companies, consultants, and researchers have developed a variety of terms and ideas to emphasize what they believe are the salient issues in a supply chain system. Indeed, the logistics industry today is a classic example of quality service (based on industry development), and further studies of logistics from the perspective of global SC relationships are needed (Chapman et al., 2003; Knemeyer & Murphy, 2004, 2005; Lambert et al., 2004). Research by Millen et al., 1999) determined that improved customer satisfaction can be attained through efficient logistics. Other research has shown that quality in the SC has the greatest influence on customer satisfaction as well as product quality (Argüelles et al., 2002).

In general, SC logistics has two different perspectives on quality: objective and subjective. Objective quality is about adapting service to the service provider-defined specifications. From this perspective, quality is an accurate measure (assessment) of all SC stages (Garvin, 1984). Subjective quality is about delivering quality to the customer. This means that SC logistics and quality is "a global judgment or attitude, concerning the superior nature of the service" (Parasuraman et al., 2004). In this dissertation, a novel objective quality measurement that includes service level rate, reliability rate, resilience rate, and robustness rate has been developed. This measurement is capable of evaluating the overall supply chain system and all members included in the system.

2.5 Performance Quantification of Complex Supply Chain Systems

Few studies focus on supply chain quality from the perspectives of service level, reliability, resilience, and robustness. Ensuring these perspectives is essential for maintaining customer satisfaction and system cost. The effective design of an SC can be achieved by designing evaluation models and incorporating them in all entities in the SC. Additionally, minimizing cost, increasing productivity, and customer satisfaction are models of common objectives of all

activities and performance aspects in the SC. Therefore, a system's performance measurements must be perceived by all members of the SCS in order to ensure service, reliability, resilience, and robustness for maintaining customer requirements. For instance, fill rate, confirmed fill rate, response delay, stock, and delay are patterns for the SCS performance metric (Kleijnen & Smits, 2003). The necessity to describe and analyze SC performance measures has been studied by several researches. For instance, Otto and Kotzab (2003) described six correlative techniques to measure the performance of an SCS: system dynamics, operations research, logistics, marketing, organization, and strategy. A non-radial network using a data envelopment analysis model was proposed by Rostamy-Malkhalifeh and Mollaeian in 2012 as a technique to evaluate the performance of an internal SC. Multiple performance metrics were recommended by Kleijnen and Smits in 2003 to measure internal processes, innovations, and finances for SC management. In the same context, Gunasekaran et al. (2001) suggested numbers performance metrics to measure the performance of suppliers, delivery, customer service, and cost of inventory and logistics in a SC management. Recently, Harrington et al. (2012) proposed a performance metric methodology to assess the degree to which network integration enablers are in place to support service SC network integration activities. Consequently, none of the previous research focused on the overall SCS performance and interactions between connected factories. However, this dissertation focuses precisely on those issues.

The concept of performance quality has significantly changed the business practice of the SCS. This began in the mid-nineties as logistics research began to analyze the capacity of logistics to improve transportation quality and thus provide greater service-level satisfaction and reliability (Mentzer et al., 2004). In fact, many companies, consultants, and researchers have developed a variety of terms and ideas to emphasize what they believe are the salient issues in the SCS. Service

level has been considered as a primary measure in the SCS in many business enterprises. For example, SL is considered an important measure at Hewlett-Packard Company (Billington et al., 2004), Procter & Gamble (Farasyn et al., 2011), and Fabric & Home Care in Western Europe (Farasyn et al., 2011).

Numerous studies have focused on developing approaches to improving the SCS service level under stochastic demand (Chu & Shen, 2010; Funaki, 2012; Li et al., 2013; Rodriguez et al., 2014; You & Grossmann, 2010; Yue and You, 2013). Most of this research is grouped under the name guaranteed service model (GSM). "GSM research, demand bounds are usually defined in terms of a service measure which reflects the percentage of time that the safety stock covers demand variation during a coverage time. This service measure is known in the literature as the Cycle-Service-Level (CSL)" (Eruguz et al., 2013). Several supply chain studies have focused on improving the GSM. For example, Eruguz et al., (2014) developed a deterministic optimization model for optimizing reorder intervals and order-up-to levels in guaranteed service supply chains. Also, Rambau and Schade (2010) developed a two-stage stochastic mixed-integer linear program with simple recourse for guaranteed service model to enhance the guaranteed service model by a recourse component and demand scenario sampling. The key difference between previous studies and the research proposed in this work is the focus on the service level. In previous studies, the cycle-service-level is used to predict the ability of the system to meet variation in demands from customers. In this dissertation, focus is on a series of linked factories, each of which has variability in processing times and time of delivery. Due to this variability, there can be delay in the supply chain system. In this dissertation, the concept of SL addresses the delay resulting from the inherent variability of the manufacturing and transportation systems.

Most systems are designed under certainty with a passive and stable design activity and therefore may become unreliable during disruption. To ensure a system's performance during disruption, most of its structures are designed with a redundant system. However, when designing in redundant systems, the life-cycle cost of the system may increase due to system redundancy (Youn et al., 2011). Recently, research has been conducted on resilience and has progressed in several fields such as psychology (Bonanno et al., 2007; Bonanno et al., 2005; Luthar, 1999; Luthar et al., 2000), ecology (Hartvigsen et al., 1998; Kerkhoff & Enquist, 2007; Webb, 2007), and management (Hollnagel, 2006; Hollnagel et al., 2007; Sheffi, 2005). Few studies have been conducted on supply chain resilience. Pettit et al. (2013) developed a measurement tool called "Supply Chain Resilience Assessment and Management," which aims to evaluate the current level of resilience of a firm. Park et al. (2011) emphasized the need for practical methods to implement resilience. Inman and Blumenfeld (2013) studied the impact of product complexity on SC resilience. Snyder et al. (2006) presented different models for the design of supply chains that are resilient to disruptions. Ponomarov and Holcomb (2009) presented an integrated perspective on resilience through an extensive review of the literature in a number of disciplines including developmental psychology and ecosystems. However, the resilience of an SC system when there are interactions between connected factories and the impact of these interactions on the overall SCS performance has been rarely studied and remains almost unexplored. This research aims to incorporate the resilience concept into SC system design, considering interactions between connected factories and the impact of these interactions on overall SCS reliability, resilience, and robustness.

2.6 Robust Design Optimization of Complex Supply Chain Systems

It is well known that traditional deterministic optimization has been successfully applied to many engineering designs in order to systematically enhance system quality and reduce life-cycle cost (Tu et al., 1999). However, variation and variability in manufacturing processes, material properties, system performance quality, and cost are acquired because of uncertainties. The existence of uncertainty in engineering system and design is initiated by the nature and complexity of processes, which raise the need for robust design optimization (RDO) in order to reduce system cost, control quality, and reduce the impact of associated uncertainty. RDO outperforms existing deterministic discrete optimization tools when dynamic conditions or uncertainty is involved in optimization problems.

RDO is a cost-efficient optimization technique used to minimize the functional variation of a system without eliminating the sources of variation. A robustness technique was first introduced by Taguchi (Hwang et al., 2001; Taguchi, 1987; Taguchi & Phadke, 1988). The Taguchi technique helps to find a robust solution that is less sensitive to unknown variations. In general, RDO can be categorized into three approaches (Yadav et al., 2010): Taguchi's experimental design (Phadke, 1995), optimization procedures based on the Taylor series expansion, and a robust design technique based on response surface methodology (Chen et al., 1999; Eggert & Mayne, 1993). The main goals of all RDO approaches are to reduce the impact of performance uncertainties (variance) about the mean values without eliminating the cause of uncertainties in order to satisfy performance targets, as shown in Figure 2.2. Generally, RDO can be expressed as equation (2.1). The objective function of RDO comes from Taguchi's definition of robust design, which minimizes variation around the mean and is constrained by the required quality or performance function.

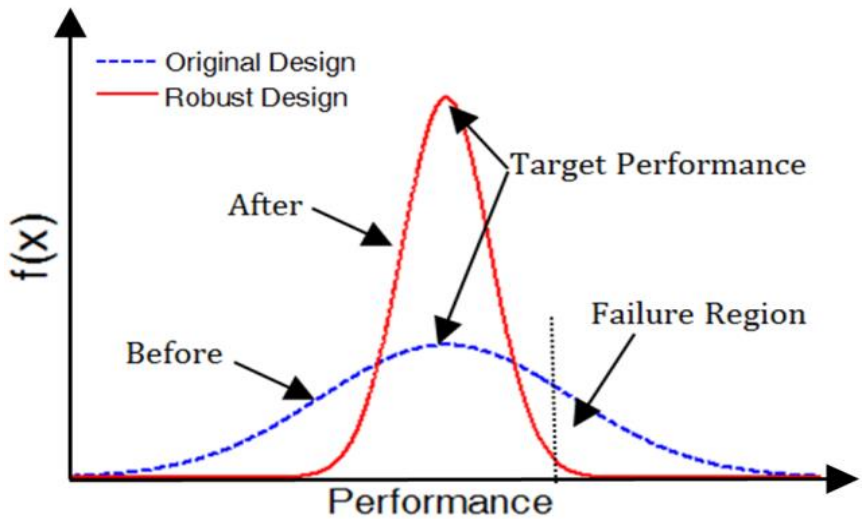

Figure 2.2. Robust design optimization concept

$$
\begin{aligned}
&\textit{Minimize} \quad \sigma^2_{f_i}(x_j) \\
&\textit{Subject to} \quad f_i(x_j) = Q_i, \; i = 1,2,...,n \\
&\qquad\qquad\quad x_j^L \le x_j \ge x_j^U, \; j = 1,2,...,J \\
&\qquad\qquad\quad x_j \ge 0
\end{aligned}
\tag{2.1}
$$

where $f_i(x_s)$ is the quality function of the ith function, $\sigma^2_{fij(xs)}$ represents its variance, Q_i is the target quality for the ith function, x_s is the sth design variable, and $x^L{}_s$ and $x^U{}_s$ are the lower and upper limits of the sth design variable, respectively.

Recently, robust design optimization has been widely applied to many engineering problems. For example, Kang and Bai (2013) investigated RDO of truss structures with uncertain-but-bounded parameters and loads. Shi et al. (2013) designed a robust configuration for a cross-docking distribution center to minimize uncertainties due to disturbances of supply. Gu et al. (2013) considered a robust concept in designing a robust servo system of a hard disk drive. Kim et al. (2013) applied RDO to optimize vibrational characteristics and weights of optical structures of aircraft. In Althoff et al. (2012), RDO is used to produce new retroaldolase catalysts from a large variety of scaffolds. RDO is also applied to optimize supercritical carbon dioxide anti-solvent

process for the preparation of 2,4,6,8,10,12-hexanitro-2,4,6,8,10,12-hexaazaisowurtzitane nanoparticles (Bayat et al., 2013).

Numerous studies in supply chain systems have aimed to reduce uncertainty in order to improve SCS robustness. For example, Pishvaee et al. (2012) addressed the problem of socially responsible supply chain network design under uncertain conditions. Pan and Nagi (2010) presented a robust SC design under uncertain demand in agile manufacturing. Simchi-Levi et al. (2013) presented a study in increasing SC robustness through process flexibility and strategic inventory. Hasani et al. (2012) modeled an SCN design under interval data uncertainty for perishable goods in agile manufacturing. Lalmazloumian et al. (2013) developed a robust optimization model for agile and build-to-order SC planning. Amin and Zhang (2013) proposed a three-stage model for a closed-loop SC configuration under uncertainty.

From the literature, it is clear that there is an urgent need to study the interaction between a connected factory of an upstream supply chain system and its impact on the overall SCS performance. Thus, the main goal of using RDO in a supply chain system is to design an SCS with inherent robustness while minimizing cost. A robust SCS can be obtained by implementing RDO and considering all entities and activity.

CHAPTER 3

MEASUREMENT OF SUPPLY CHAIN SYSTEM SERVICE LEVEL

3.1 Introduction

A rapidly growing discipline involving the supply chain has changed the approach by which industries generate a suitable service in order to meet customers' needs. This chapter introduces a new approach to calculate the service level rate of any given SCS and consists of multiple factories and routes that could be connected in series or/and parallel. The rest of this chapter is organized as follows. Section 3.2 develops an SCS service level rate. Section 3.3 presents two case studies: a series supply chain system and a complex supply chain system. Finally, conclusions are addressed in Section 3.4.

3.2 Supply Chain System Service Level Rate

The supply chain is a new and rapidly growing discipline that is driving and changing the philosophy by which industries meet the needs of customers and provide appropriate service to ensure customer satisfaction. Previous studies in the literature have mainly focused on individual factories in a supply chain system. Performance of the overall supply chain system and interactions among connected factories have not been studied. To design a robust SCS, performance measurement and analysis need to be applied throughout its development process. Furthermore, all activities and performance aspects in the SCS should be dedicated to common objectives such as minimizing the cost of failures, and increasing productivity and customer satisfaction. Also, all SCS members should understand the network's performance measurements.

Progression and development of a supply chain system is affected by not only internal factors but also numerous external factors (i.e., growing globalization, information availability, global trade, ecological concerns, etc.). Therefore, SCS output should be measured and compared

with a qualified set of performance measures. To control the performance of an SCS, the process parameters of the factory must be kept within a constant range limit. By doing so, comparisons of target performances and actual performances are possible. Once comparisons are completed, specific identified processes in factories can be targeted in order to improve the SC performance. For example, a long lead time can be caused by a weak facility layout, which would ultimately affect factory performance and overall SCS performance.

By using an appropriate set of measures, the overall supply chain system performance can be monitored closely. Successive improvements can be applied to each entity in the SC to regulate overall SCS improvements. Since the SCS could consist of multiples factories and levels, as shown previously in Figure 2.1, it is critical to ask which factory in the network should be enhanced and to what degree these factory improvements will enhance the overall SCS. Thus, it is important to identify an effective measure that can reflect and measure the supply network performance to achieve customer satisfaction. Factory service level rates and the overall SC can be used to identify customer satisfaction, and their calculation is based on the factory performance. To illustrate, the service level (SL) rate can be defined as the probability of completing all required jobs at time (t) before the due time (T), as shown in Figure 3.1 and statistically expressed in equation (3.1).

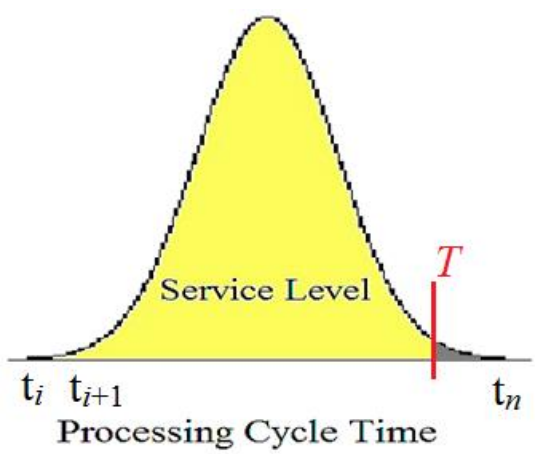

Figure 3.1. Service level rate phenomenon

$$SL = Pr(t_1 + t_2 + ... + t_n \leq T) \tag{3.1}$$

Mathematically, the SL rate of factories, routes, and the overall supply chain system is the ratio of the total cycle time minus the cumulative delay to the total cycle time. Total cycle time is the cumulative time that a batch spends in all factories and routes to reach the final point (customers). The cumulative unexpected delay is the cumulative delay due to uncertainties in the factory processing time and transportation time. The service level rate can be obtained using equations (3.2) to (3.6). Equation (3.2) is used to calculate the SL rate, equation (3.3) is used to calculate the total cycle time without considering delay time (TCT^T), equation (3.4) is used to calculate total delay time ($C\varepsilon_{i,j}$) due to variability and uncertainty in the SCS, equation (3.5) is used to calculate total delay time ($DT_{i,j}$) due variability, and equation (3.6) is used to calculate the variability ($D_{i,j}$).

$$SL_{i,j} = \frac{TCT^T - C\varepsilon_{i,j}}{TCT^T} \tag{3.2}$$

$$TCT^T_{i,j} = TCT^T_{i,k} + CT^T_{i,j} \tag{3.3}$$

$$C\varepsilon_{i,j} = f_{i,j}(Combined\ standard\ deviation\ of\ entities\ in\ the\ network) + DT_{i,j} \tag{3.4}$$

$$DT_{i,j} = D_{i,j}(Combined\ delay\ of\ entities\ in\ the\ network) \tag{3.5}$$

$$D_{(k,j-1,i,j)} = \begin{cases} if \quad CT_{k,j-1} > CT_{i,j}, D_{i,j} = CT_{k,j-1} - CT_{i,j} \\ 0 \quad otherwise \end{cases} \tag{3.6}$$

where $SL_{i,j}$ represents the SL rate of entity i in level j in the supply chain system, TCT^T is the total cycle time to complete the required job, $CT^T_{i,j}$ is the cycle time at entity i in level j, $C\varepsilon_{i,j}$ is the cumulative unexpected delay in entity i at level j in the SCS, $f_{i,j}$ is a function that combines the

standard deviations of two entities in an SCS (Krishnan et al., 2009, provided an example that shows how the convolutions of two distribution functions can be calculated), $DT_{i,j}$ is a function of cumulative delay due to unbalanced entities in the network, and $D_{i,j}$ is the waiting time that entity i at level j spent waiting for products from the previous factory k in the previous level j-1.

3.3 Case Studies

Here the proposed methodology is demonstrated by addressing two case studies: the first, a supply chain system consisting of series entities, and the second, a complex SCS consisting of series and parallel entities. Both of these cases are SCSs with unbalanced entities, which means each entity has different processing and transportation times. Two strategies were implemented (balanced strategy and increasing due date) in order to study how uncertainty can affect SCSs.

3.3.1 Case Study One

Case study one considers a company that operates three manufacturing plants worldwide across all major geographic markets, and the factories are in series, as shown in Figure 3.2.

Figure 3.2. Schematic of supply chain network

The SCN for the company can be divided into four major levels:

- **Level 1**: Production of raw petrochemical materials used in different products.
- **Level 2**: Production of petrochemical materials to be used in producing multiple products.
- **Level 3**: Production of final products.
- **Level 4**: Customers.

In this case study, raw material is transported to factory M_1. Then products are shipped from factory M_1 to M_2, and after further processing, they are shipped to factory M_3 (Figures 3.2 and 3.3). The mean time to process a batch and the variability associated with processing as well as transportation is provided in Table 3.1.

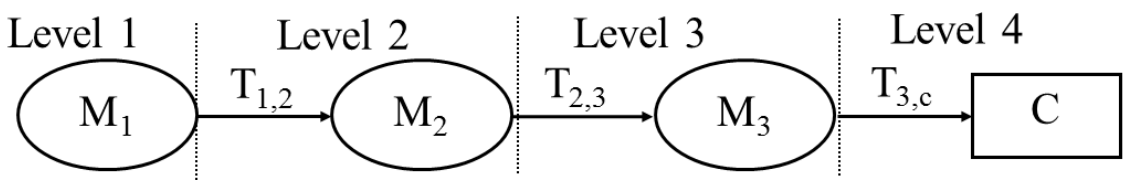

Figure 3.3. Supply chain network levels

TABLE 3.1

DESIGN PARAMETERS FOR CASE ONE

SCN Member	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Factory 1 (M_1)	85	20
Factory 2 (M_2)	75	11
Factory 3 (M_3)	80	15
Transportation between M_1 and M_2	110	40
Transportation between M_2 and M_3	120	70
Transportation between M_3 and C	111	30

In this study, it is assumed that if there is a transportation delay between levels, the factory at the next level will wait until the materials or products have arrived. Also, products cannot be shipped from one factory to the next until the required quantity for a batch is completed.

First, the proposed mathematical model was implemented to this unbalanced SCN in order to measure the initial system performance by applying equations (3.2) to (3.6). The cycle time for all entities in the supply chain was obtained using the SCN MATLAB model. The total cycle time was then calculated by using a recursive equation (equation [3.3]). Next the expected delay for each entity in the SC was calculated by using equations (3.5) and (3.6). Table 3.2 represents the current service level rates for each entity in the SCN. The total expected delay for the supply chain system was then calculated by using equation (4). Then the balanced and increasing due date strategies were implemented in order to enhance the system service level rate.

TABLE 3.2

SERVICE LEVEL RATES FOR EACH ENTITY

SCN Member	**Uncertainty (Time Delay) (hr/batch)**	**Service Level Rate (percent)**
Factory 1 (M_1)	20	96.56
Transportation between M_1 and M_2	45	92.27
Factory 2 (M_2)	81	86.05
Transportation between M_2 and M_3	118	79.55
Factory 3 (M_3)	161	72.43
Transportation between M_3 and C	166	71.54

Table 3.2 illustrates uncertainties and service level rates of the SCN for the initial data. Figure 3.4 shows that the SL rate of the SCN decreases monotonically when traversing from the input point to the output point in the network, and there is a negative correlation between the SL

rates with SC levels. For example, the SL rate of factory M_1 is 96.56%, whereas the SL rate of factory M_2 is decreased by 10.52% to 86.04%, due to the differences in processing times between factories and associated uncertainties. The overall service level rate for the SCN is 71.54%. This means that the SCN does not meet the required service level rate of 90%. One method to achieve the desired service level rate is to use the balanced strategy in order to improve SCN performance.

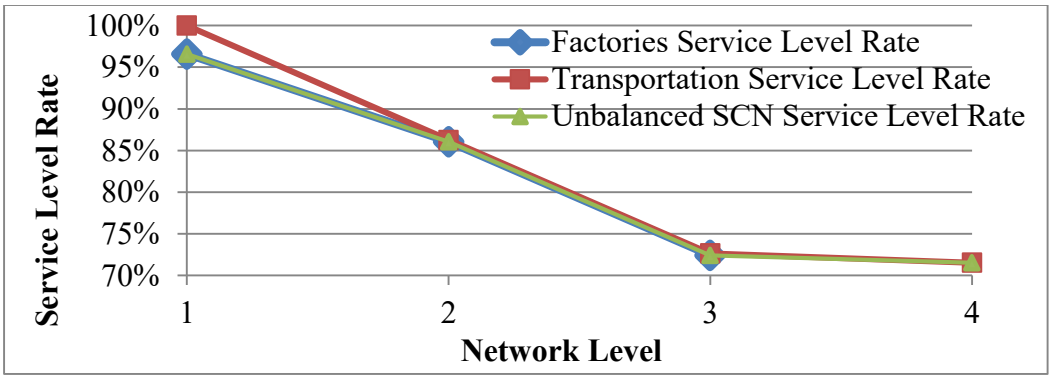

Figure 3.4. Initial service level rate of all levels in SCN

3.3.1.1 Balanced Strategy for Case One

As the first step to achieving a higher service level, the mean time of processing was increased to the highest mean time of 120 hours per batch. This allowed each factory to have slack time and a late start for some factories. However, this also balanced the mean time for processing each batching. Thus, to implement the balanced strategy, the processing and transportation times were increased to the highest mean time value (120 hours per batch) from Table 3.1, while not changing the variability in the system. The results are shown in Table 3.3.

TABLE 3.3

DESIGN PARAMETERS FOR BALANCED STRATEGY

SCN Member	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Factory 1 (M_1)	120	20
Factory 2 (M_2)	120	11
Factory 3 (M_3)	120	15
Transportation between M_1 and M_2	120	40
Transportation between M_2 and M_3	120	70
Transportation between M_3 and C	120	30

Just as in the treatment of the unbalanced data set, the mathematical model for the balanced model is implemented to assess the initial system performance by following the same procedure as in the unbalanced case. Table 3.4 illustrates service level rates for each entity in the SCN. Thus, in this case, the required SL rate has not been obtained. Figure 3.5 illustrates the case one balanced strategy SL rate for all levels in the SCN.

TABLE 3.4

BALANCED STRATEGY SERVICE LEVEL RATES OF EACH ENTITY

SCN Member	Uncertainty (Time Delay) (hr/batch)	Service Level Rate (percentage)
Factory 1 (M_1)	20	97.22
Transportation between M_1 and M_2	45	93.79
Factory 2 (M_2)	46.12	93.59
Transportation between M_2 and M_3	84	88.34
Factory 3 (M_3)	85.27	88.16
Transportation between M_3 and C	90.4	87.44

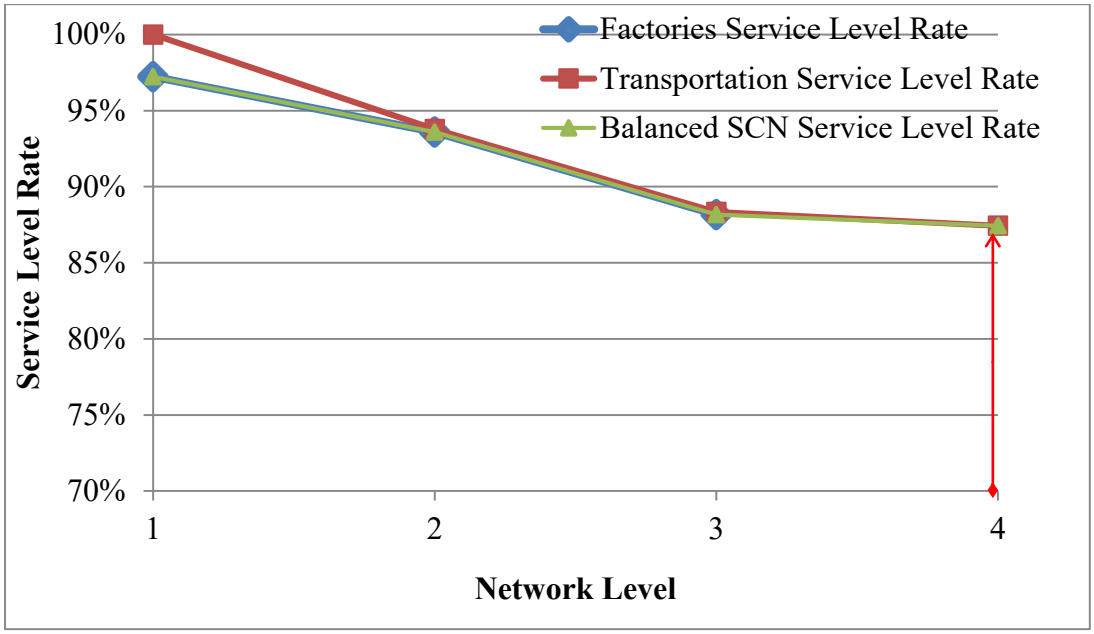

Figure 3.5. Balanced strategy service level rate for all levels

It can be seen that by implementing the balanced strategy, the service level rate of the SCN is improved due to balanced processing and transportation times. In comparison to the unbalanced SCN, the service level rate at factory M_2 has improved from 86.04% to 93.62% due to the implementing balanced strategy. Moreover, the overall service rate has improved to 87.44%. However, it does not meet the required service level rate of 90% due to uncertainty in the processing time. Thus, in order to meet the requirement of SL rate, further adjustments must be made.

3.3.1.2 Increasing Due-Date Strategy for Case One

From previous studies and analysis, it can be concluded that processing time uncertainties are one of the main reasons for the reduction of the service level rate of an SCN. Also, it is clear that SL rate decreases monotonically from one level to the next, and the SL rate achieved at any

level is dependent on the SL rate at the previous level. To increase and attempt to achieve the required SL rate, the due dates were increased to the largest mean processing time. In this case study, the mean time available for all jobs was increased by deferring the due date from 581 hours for one batch to 1,653.5 hours. A model with the new available time was developed and implemented using MATLAB. In this case study, the service level rate improved to 90%, as shown in Figure 3.6. When comparing SL rates of increasing the due date strategy with initial system service level rate, it can be seen that the SL rate of factories and routes are similar but are different at the last point in the system. To illustrate, the SL rate of factory one is 96.56%, route one is 92.27%, factory two is 86.05%, route two is 86.05%, and factory three is 72.43% in the initial system status (unbalanced) and the increasing due date strategy. But the last entity in the system (route three) is 71.54% in the initial system and 90% in the increasing due date strategy.

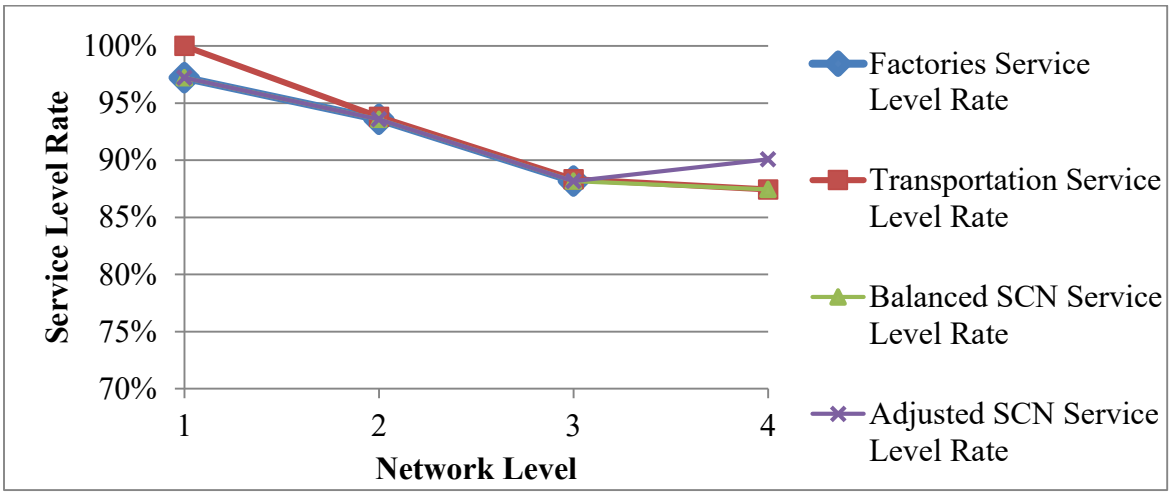

Figure 3.6. Increasing due date strategy results

By completing this case study, it is clear that the proposed service level rate for supply chain systems can measure the performance of a series system. Also, the SL rate of SCSs can be improved by applying balanced and increasing due date strategies. The initial SL rate of the system

is 71.54%, but when implementing a balanced strategy, this increased to 87.44% and when implementing increasing due date strategy, this increased to 90%.

3.3.2 Case Study Two

The proposed supply chain network in this case study consisted of connected parallel and series factories. There were five levels and 22 entities comprised of 10 factories and 12 routes. This study was performed to test the efficacy of the preformed methodology. Figure 3.7 represents the complex supply chain system, where M_{ij} denotes factory i at level j and $T_{(k,j-1)(i,j)}$ denotes transportation (route) from previous factory k at level j-1 to factory i at level j. In this SCN, it was assumed that factories could not start the required job until receiving all required parts from previous-level factories. For example, factory 4 ($M_{1,2}$) will not start until it receives the required parts from factory $M_{1,1}$ and factory $M_{2,1}$. For purposes of this study, the collected data (design parameters) were assumed to be normally distributed. Their means and standard deviations are shown in Tables 3.5 and 3.6. To solve this case study, the SCS was modeled on MATLAB 2012a.

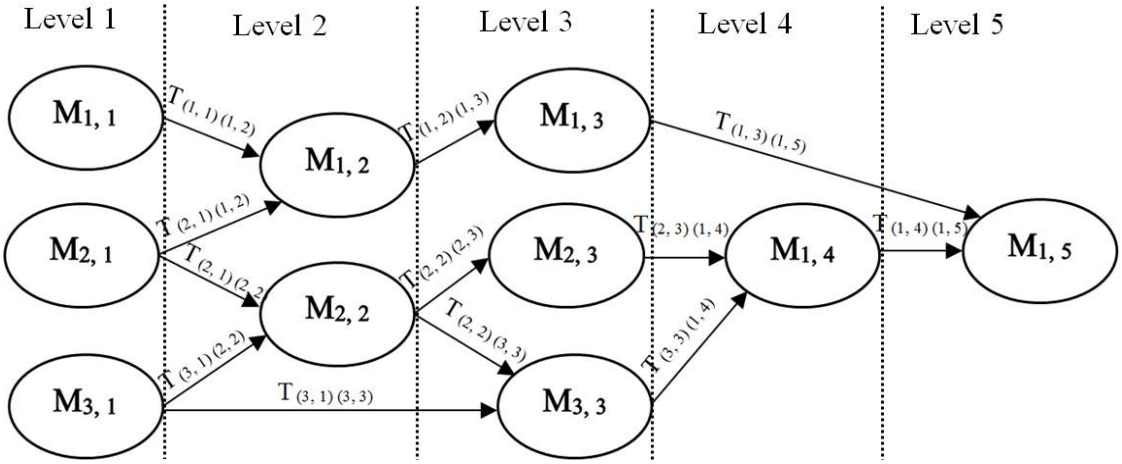

Figure 3.7. Schematic of case two complex SCN

TABLE 3.5

CASE TWO FACTORY DESIGN PARAMETERS

SCN Factory	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Factory 1 ($M_{1,1}$)	85	20
Factory 2 ($M_{2,1}$)	79	11
Factory 3 ($M_{3,1}$)	91	15
Factory 4 ($M_{1,2}$)	83	13
Factory 5 ($M_{2,2}$)	80	17
Factory 6 ($M_{1,3}$)	85	22
Factory 7 ($M_{2,3}$)	88	18
Factory 8 ($M_{3,3}$)	77	21
Factory 9 ($M_{1,4}$)	90	15
Factory 10 ($M_{1,5}$)	76	19

TABLE 3.6

CASE TWO TRANSPORTATION DESIGN PARAMETERS

SCN Route	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Route 1 ($T_{(1,1)(1,2)}$)	30	11
Route 2 ($T_{(2,1)(1,2)}$)	28	8
Route 3 ($T_{(2,1)(2,2)}$)	19	9
Route 4 ($T_{(3,1)(2,2)}$)	22	6
Route 5 ($T_{(3,1)(3,3)}$)	20	4
Route 6 ($T_{(1,2)(1,3)}$)	26	7
Route 7 ($T_{(2,2)(2,3)}$)	18	6
Route 8 ($T_{(2,2)(3,3)}$)	20	8
Route 9 ($T_{(1,3)(1,5)}$)	25	9
Route 10 ($T_{(2,3)(1,4)}$)	23	5
Route 11 ($T_{(3,3)(1,4)}$)	20	10
Route 12 ($T_{(1,4)(1,5)}$)	17	7

First, the SCN mathematical model was implemented in MATLAB to measure the initial system performance. The procedures followed were similar to those in case study one. Table 3.7 shows the computed SL rate for all factories when the SCN is unbalanced (current design). Table 3.8 provides the computed SL rate for routes in the unbalanced SCN. Table 3.9 illustrates the overall SCN uncertainties and SL rates for each level in the unbalanced SCN. As shown, the SL rate of the SCN decreases from the first level to the fifth level in the network. For example, in Table 3.9, the service level rate for level 1 is 96.26%, whereas in level 2, the SL rate is decreased by 12.03% to 84.23%. This decrease is caused by different processing and transportation times between factories and associated uncertainties. The SL rate of the SCN is very low at 39.09%. In the next section, a different scenario was applied by balancing all transportation and processing times to analyze factors that had the highest impact on service level of the SCN.

TABLE 3.7

CASE TWO - FACTORY SERVICE LEVEL RATE

SCN Factory	Time Variation (hr/batch)	Service Level Rate (percentage)
Factory 1 ($M_{1,1}$)	19	96.26
Factory 2 ($M_{2,1}$)	11.34	97.75
Factory 3 ($M_{3,1}$)	15.37	96.96
Factory 4($M_{1,2}$)	79.6284	84.23
Factory 5 ($M_{2,2}$)	93	81.64
Factory 6 ($M_{1,3}$)	146.21	71.05
Factory 7 ($M_{2,3}$)	162.16	67.89
Factory 8 ($M_{3,3}$)	162.29	67.86
Factory 9 ($M_{1,4}$)	230.58	54.34
Factory 10 ($M_{1,5}$)	307.56	39.09

TABLE 3.8

CASE TWO - TRANSPORTATION SERVICE LEVEL RATE

SCN Route	Time Variation (hr/batch)	Service Level Rate (percentage)
Route 1 ($T_{(1, 1)(1, 2)}$)	76.10	84.93
Route 2 ($T_{(2, 1)(1, 2)}$)	65.13	87.10
Route 3 ($T_{(2, 1)(2, 2)}$)	75	85.18
Route 4 ($T_{(3, 1)(2, 2)}$)	86	82.98
Route 5 ($T_{(3, 1)(3, 3)}$)	87.04	82.76
Route 6 ($T_{(1, 2)(1, 3)}$)	137.37	72.79
Route 7 ($T_{(2, 2)(2, 3)}$)	155.53	69.20
Route 8 ($T_{(2, 2)(3, 3)}$)	154.34	69.44
Route 9 ($T_{(1, 3)(1, 5)}$)	207	59.02
Route 10 ($T_{(2, 3)(1, 4)}$)	227.04	55.04
Route 11 ($T_{(3, 3)(1,4)}$)	221	56.31
Route 12 ($T_{(1, 4)(1, 5)}$)	304	39.86

TABLE 3.9

CASE TWO - SERVICE LEVEL RATE OF EACH LEVEL

SCN Level	Time Delay (hr/batch)	SCN Service Level Rate (percentage)
Level 1	19	96.26
Level 2	80	84.23
Level 3	162.29	67.86
Level 4	230.58	54.345
Level 5	307.56	39.09

3.3.2.1 Balanced Strategy for Case Two

In this strategy, the complex SCN service level rate was enhanced by using a balanced time strategy. Thus, the factory and transportation processing times are balanced and identical. Processing and transportation times are equal to the highest processing or transportation time in the SCN, which is 91 hours per batch. However, processing and transportation time uncertainties are different because each factory and route has different characteristics, as shown previously in Tables 3.5 and 3.6. For example, the expected delay while using the route between factories 1 and 4 (route 2) is 11 hours per batch, while the expected delay while using the route between factories 9 and 10 (route 12) is 7 hours per batch. A mathematical simulation model in MATLAB was used to perform this strategy. The simulation results, shown in Tables 3.10 to 3.12, illustrate the SL rates for factories in the balanced SCN. Table 3.11 shows SL rates for transportation in the balanced SCN. Table 3.12 illustrates overall SCN SL rates for each level in the balanced SCN.

TABLE 3.10

CASE TWO - BALANCED STRATEGY SERVICE LEVEL RATE OF FACTORIES

SCN Factory	Time Variation (hr/batch)	Service Level Rate (percentage)
Factory 1 ($M_{1,1}$)	20	97.52
Factory 2 ($M_{2,1}$)	11	98.62
Factory 3 ($M_{3,1}$)	15	98.21
Factory 4 ($M_{1,2}$)	23	97.54
Factory 5 ($M_{2,2}$)	13.5	97.02
Factory 6 ($M_{1,3}$)	14.22	96.3
Factory 7 ($M_{2,3}$)	16.16	96.14
Factory 8 ($M_{3,3}$)	15.54	95.82
Factory 9 ($M_{1,4}$)	26.28	95.01
Factory 10 ($M_{1,5}$)	22.18	94.79

TABLE 3.11

CASE TWO - BALANCED STRATEGY SERVICE LEVEL RATE OF TRANSPORTATION

SCN Route	Time Variation (hr/batch)	Service Level Rate (percentage)
Route 1 ($T_{(1, 1)(1, 2)}$)	27.2	97.07
Route 2 ($T_{(2, 1)(1, 2)}$)	23	98.23
Route 3 ($T_{(2, 1)(2, 2)}$)	23.59	98.25
Route 4 ($T_{(3, 1)(2, 2)}$)	35	98.01
Route 5 ($T_{(3, 1)(3, 3)}$)	29.18	98.13
Route 6 ($T_{(1, 2)(1, 3)}$)	32.49	97.43
Route 7 ($T_{(2, 2)(2, 3)}$)	36.16	96.92
Route 8 ($T_{(2, 2)(3, 3)}$)	30	96.88
Route 9 ($T_{(1, 3)(1, 5)}$)	34.04	96.13
Route 10 ($T_{(2, 3)(1, 4)}$)	37.21	96.05
Route 11 ($T_{(3, 3)(1,4)}$)	38	95.42
Route 12 ($T_{(1, 4)(1, 5)}$)	42.41	95.44

TABLE 3.12

CASE TWO - BALANCED STRATEGY SERVICE LEVEL RATE OF EACH LEVEL

Supply Chain Level	Time Delay (hr/batch)	Service Level Rate (percentage)
Level 1	20.29	97.52
Level 2	26.3	96.75
Level 3	34.23	95.82
Level 4	41	95.01
Level 5	43	94.79

Results show that the service level rate of the SCN declines from the first to the fifth levels in the network. This decrease is due to processing and transportation uncertainties that lead to an

SL rate of 94.79% in the balanced SCN. Moreover, it can be seen that the SL rate of the SCN is improved due to balanced processing and transportation times. In comparison to an unbalanced SCN, the service level rate at factory 8 has improved from 67.86% to 95.82% due to implementing a balanced strategy. Moreover, the overall service rate has improved to 94.79%. Since the service level rate is higher than the required service level rate of 90%, there is no need to implement the increasing due date strategy to this case.

Comparing both balanced and unbalanced SCNs from previous studies and analyses, it can be concluded that transportation and processing time uncertainties are one of the main reasons for reduction of the service level rate in the SCN. Also, it is clear that SL rates from one level to the next are dependent on each other. By applying the simulation model, the higher SL rate can be obtained when the SCN unbalanced is 96.26% for level one with a time delay of about 19 hours per batch. And the lowest service level rate is 39.09% for level 5 when the time delay is around 307.56 hours per batch. In contrast, when the SCN is balanced, the SL rate for level one increases up to 97.52% instead of 96.26%, and the lowest SL rate of the overall SCN is 94.79%.

By completing the complex supply chain system case study, it is clear that the proposed service level rate for SCSs can measure the performance of any factory SCS. Also, the service level rate of the SCSs can be improved by applying a balanced strategy. The initial service level rate of the system is 39.09%, but when applying the balanced strategy, this increased to 94.79%.

3.4 Conclusion

As more and more companies are involved in outsourcing and building factory supply chains, there is an urgent need to develop the concept and understanding in factory-to-factory supply chain systems. This chapter focused its attention on introducing service level rates that can measure the performance of each entity in the system and overall SCS performance using the

developed SL rate measure. This research has shown the impact of balanced and unbalanced SCSs on the service level at the final factory. It also explored strategies to improve the SL rates. In summary, this research developed an effective measure that can reflect and measure any SCS performance and studied the effects of uncertainty and delays introduced by production and transportation on the overall performance of the SCS. By completing this study, the first thrust of this dissertation was completed and the first two key research questions—(1) How do you measure the performance of the whole SCS that consists of multiple types of entities (factories and routes)? and (2) How do you measure the performance of different types of factory those produce different products with different quantities using one unique measure?—were addressed.

CHAPTER 4

ASSURANCE OF SYSTEM SERVICE LEVEL ROBUSTNESS IN COMPLEX SUPPLY CHAIN NETWORKS

4.1 Introduction

This chapter presents the study of the uncertainty effect introduced by factory service level rates on the robustness of overall supply chain network performance. It also presents a novel robust design optimization methodology to derive designs of factory SL rates in order to satisfy the SL rate requirement of the system and ensure its robustness. The objective here was to design an upstream supply chain system with the SL rate at each layer being optimally allocated so that an optimized system SL rate with a desired robustness could be ensured when subjected to uncertainties. After completing Chapter 3 and applying balanced and increasing due date strategies, further analyses were performed to find an advanced systematic and efficient method to design in order to achieve the overall SL rate. From the analysis in Chapter 3, after applying the balanced and increasing due date strategies in many cases, it was not reasonable to extend the due date because this extension would impact customer satisfaction. For this reason, the RDO was implemented in order to study the SCN performance in attaining an optimal approach. In addition, these balanced and increasing due date strategies can be cumbersome because it is necessary to test for different conditions before arriving at a feasible solution.

The optimal design of a supply chain can be obtained using RDO, which is a technique developed to guarantee a desired quality of system designs by minimizing performance variability. RDO aims to qualify the performance of engineered systems by regulating design characteristics and constraints for robustness by taking variability and uncertainties involved in the process into consideration. Numerous studies have been reported in the literature to deal with uncertainties in

practical engineered system designs (Du & Chen, 2004; Wang et al. 2011; Youn & Wang, 2009). This study employs the RDO technique for optimal design of an upstream supply chain system to enhance system service level rate and ensure its robustness. The rest of this chapter is organized as follows. Section 4.2 introduces RDO and develops an RDO model for a complex SCS. Section 4.3 develops a methodology in order to assure the SL rate of an SCS using RDO. Section 4.4 presents two case studies with a multi-level multiple factory supply chain network to demonstrate the efficacy of the proposed methodology. Finally, conclusions are addressed in Section 4.5.

4.2 Robust Design Optimization for Service Level in Supply Chain Networks

The concept of RDO has been widely studied in numerous engineering fields. Its primary aim relative to service level is to design a supply chain system with inherent robustness by implementing robust design optimization in factories in the supply chain network. RDO outperforms existing deterministic discrete optimization tools when dynamics or uncertainty is involved in optimization problems. When using RDO for SL optimization, the objective is to reduce variability between factories and associated uncertainties in the SCS and control the overall supply chain SL rate. Uncertainties and variability in the SC can be divided into three types as shown in Table 4.1.

TABLE 4.1

TYPES OF UNCERTAINTIES AND VARIABILITY IN SUPPLY CHAIN SYSTEMS

Type	Description
Internal	Random uncertainties and variability in manufacturing a product.
External	Random uncertainties and variability in raw material supply availability and transportation between factories.
Factory to Factory	Random uncertainties and variability between factory service level rates.

Figure 4.1 shows the robust supply chain system distribution. The goal of RDO is to reduce uncertainties (standard deviation) about the mean values without eliminating the cause of uncertainties, as shown here.

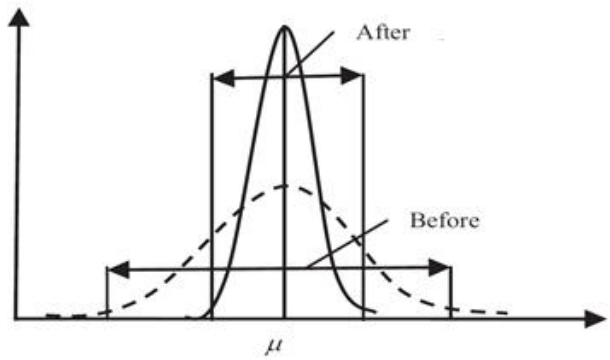

Figure 4.1. Robust supply chain system distribution

The robustness concept was first introduced by Taguchi (1987) and Taguchi and Phadke (1988). As mentioned previously, the Taguchi technique helps to find a robust solution that is less sensitive to unknown variations. Recently, many engineering problems have abeen solved by the using robustness concept. Kang and Bai (2013) investigated robust design optimization of truss structures with uncertain-but-bounded parameters and loads. Shi et al. (2013) designed a robust configuration for a cross-docking distribution center to minimize uncertainties due to disturbances of supply. Gu et al. (2013) considered robustness in designing a robust servo system of a hard disk drive. More detailed information on general RDO can be obtained from the work of Chen et al. (1999), Renaud (1997), and Yadav et al., 2010). To the best of our knowledge, none of the previous research has considered, applied, or modeled RDO to supply chain systems consisting of multiple factories and levels. Given the advantages of RDO in reducing uncertainties and improving system robustness, in this research a generic RDO model was developed and applied to different case studies, as discussed in Section 4.4. The objective of this model was to assure the service level rate in any SCS and reduce uncertainties while considering cost and customer satisfaction

simultaneously. To assure the required SL rate, the objective function of this model minimizes uncertainty, delay, and cycle time. The required service level rates are set as constraints in the model. Generally, RDO for the SL mathematical model can be expressed as

$$\begin{aligned} &Minimize \quad \sigma^2_{TCT_{i,j}(x_s)} + \mu_{TCT_{i,j}(x_s)} + \zeta_{i,j} \\ &Subject\,to \quad M_{i,j}(x_s) \geq Q_{i,j}, \; i = 1,2,...,I \\ &\qquad\qquad x_s^L \leq x_s \leq x_s^U \quad , \; j = 1,2,...,J \\ &\qquad\qquad x_s \geq 0 \qquad\qquad , \; s = 1,2,...,S \end{aligned} \tag{4.1}$$

where, $TCT_{ij}(x_s)$ is the total cycle time function of the ith entity on level j, $\sigma^2_{TCTi,\,j(xs)}$ represents its variance, $\mu_{TCTi,\,j(xs)}$ represents its mean, $\zeta_{i,j}$ is the delay function of the ith entity on level j, $M_{ij}(x_s)$ is the SL rate function of the ith factory on level j, $Q_{i,j}$ is the target SL rate for the ith factory on level j, x_s is the sth design variable, and $x^L{}_s$ and $x^U{}_s$ are the lower and upper limits on the sth design variable, respectively.

4.3 Assurance of System Service Level Rate in Supply Chain Networks

A supply chain network with factories feeding other factories can be modeled as a complex system consisting of entities in parallel and in series, such as factories, routes, and distribution centers. The supply chain system can be modeled as a function that illustrates network output and status. Each member in the network can be described as a function defining the status of the factories, which can be linear or/and nonlinear. The function must describe required jobs to complete one batch in a limited period of time. As emphasized in Chapter 3, the service level rate is capable of measuring the performance of each factory as well as the overall network. As a result, in this research, different functions were developed to describe each member in the network. As shown in Chapter 2, a complex SCN can have three types of members: (1) factories, (2) routes, and (3) customers.

The service level rate for SCN entities can be calculated based on time, since time is an important factor for each entity. To illustrate, it is important for factory entities to meet the required demand on time and provide supplies to the next entity within a specified time frame. Also, time is vital for route entities because it is important to transport a certain number of products in a specified period of time. The SL rate of an SCN can be expressed as a function of accumulated time to complete one batch (cycle time to finish one product). In general, SL rates for all members in the network and in the overall network are based on completing the required job on time, as shown previously in equation (4.1). A robust supply chain system SL rate for factories, routes, and the overall network can be obtained by using equations (3.2) to (4.1) and applying the procedure, as shown in Figure 4.2. Using mathematical modeling that utilizes different functions to describe each entity in the SCS, the robust service level rate of all entities and overall SCS can be obtained in the following nine steps:

Step 1: Collect cycle time from all entities in the supply chain, including factories, transportation, distribution, etc.

Step 2: Determine the time distribution function, mean, and standard deviation, based on collected data.

Step 3: Use Monte Carlo simulation to generate samples for all entities.

Step 4: Calculate cycle time for all entities in the supply chain $CT_{i,j}$.

Step 5: Calculate total cycle time in the supply chain when there is no variance, which can be considered as target cycle time TCT^T (see equation [3.3]).

Step 6: Calculate expected delay due to unbalanced entities (factory, transportation time) $DT_{i,j}$ (see equations [3.5] and [3.6].

Step 7: Calculate total expected delay $C\varepsilon$ for all entities and overall supply chain system (see equation [3.4]).

Step 8: Calculate service level rate $SL_{i,j}$ for each entity and for the supply chain (see equation [3.2]).

Step 9: Apply RDO using equation (4.1) to achieve the required service level rate for the overall supply chain system.

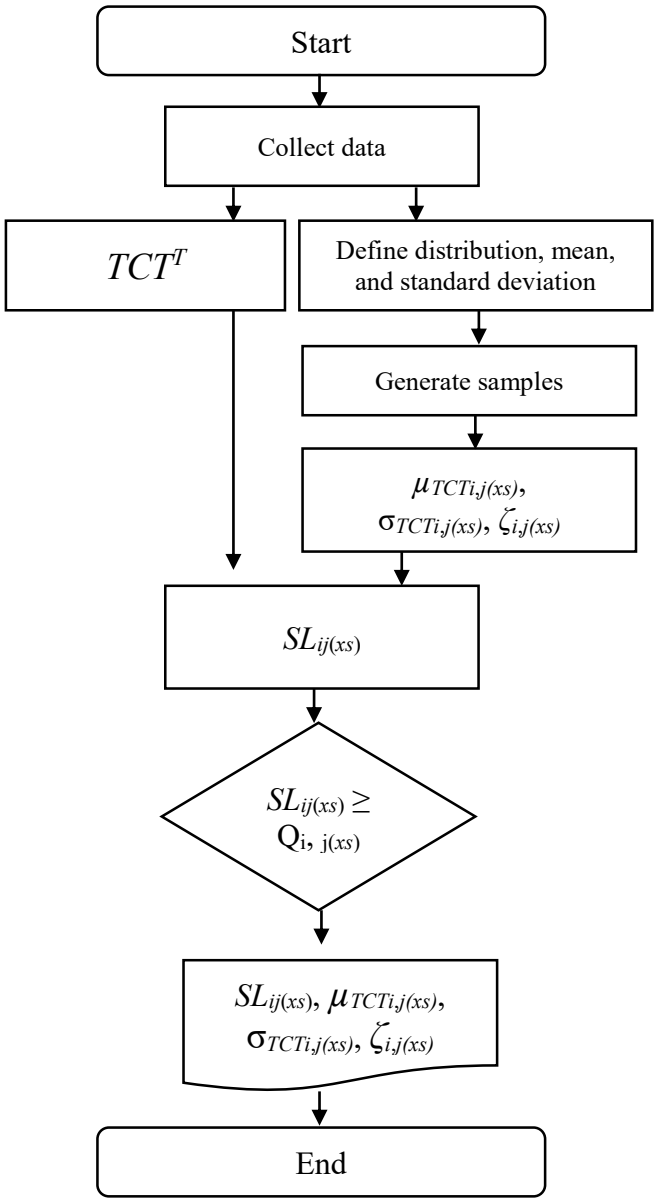

Figure 4.2. Robust SCN design procedure

4.4 Case Studies

This section presents a demonstration of the proposed methodology by addressing two case studies. The first is a supply chain system consisting of entities in series; the second is a complex SCS consisting of series and parallel entities. Both of these cases are SCSs with unbalanced entities, which means each entity has different processing and transportation times. Then RDO is implemented in order to achieve the required service level rate. Finally, results are analyzed and compared in order to select the best solution. MATLAB 2012a was used to obtain the results. The SC of these case studies is similar to case studies presented previously in Chapter 3 in that results of RDO can be compared with the balanced strategy and the increasing due date strategy.

4.4.1 Case Study One

Case study 1, considers the case of a company that operates three manufacturing plants worldwide across all major geographic markets. Here, the factories are in series, as shown in Figure 4.3. Raw material is transported to factory M_1, and products are shipped from factory M_1 to M_2, and after further processing, they are shipped to factory M_3. The mean time to process a batch and the variability associated with processing as well as transportation is provided in Table 4.2.

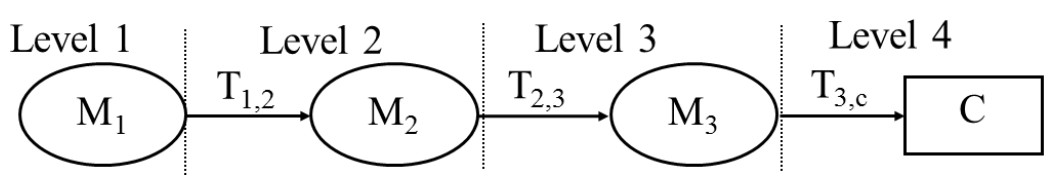

Figure 4.3 Supply chain system

The SCN for the company can be divided into four major levels:

- **Level 1**: Production of raw petrochemical materials used in different products.
- **Level 2:** Production of petrochemicals material to be used in producing multiple products.

- **Level 3**: Production of final products.
- **Level 4**: Customers.

In this study, it is assumed that if there is a transportation delay between levels, the factory at the next level will wait until materials or products have arrived. Also, products cannot be shipped from one factory to the next until the required quantity for a batch is completed.

TABLE 4.2

DESIGN PARAMETERS FOR CASE ONE

SCN Member	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Factory 1 (M_1)	85	20
Factory 2 (M_2)	75	11
Factory 3 (M_3)	80	15
Transportation between M_1 and M_2	110	40
Transportation between M_2 and M_3	120	70
Transportation between M_3 and C	111	30

First, the proposed mathematical model was applied to this unbalanced SCN in order to measure the initial system performance based on steps 4 to 8 and applying equations (3.2) to (4.1). Using the SCN MATLAB model, the cycle time for all entities in the supply chain was obtained. The total cycle time was then calculated by using recursive equation (3.3). The expected delay for each entity in the SC was calculated next by using equations (3.5) and (3.6). Table 4.3 represents the initial service level rates for each entity in the SCN, irrespective of its impact. The total expected delay for the SCS was then calculated by using equation (3.4). Based on the expected delay for each entity and the cycle time for each entity, the effective service level rate for each entity in the SCS was determined using equation (3.2). RDO was then applied to the model using equation (4.1) to achieve the required system's SL rate. The objective of this case study was to

minimize total cycle time, uncertainty, and delay for each entity and for the overall SCS. Constraints in the optimization model were the required SL rate for each entity in the SCS and for the overall SCS.

TABLE 4.3

CASE ONE - INITIAL SERVICE LEVEL RATE FOR EACH ENTITY IN SCN

SCN Member	Time Delay (hr/batch)	Service Level Rate (percentage)
Factory 1	20	96.56
Transportation between M_1 and M_2	80	86.27
Factory 2	81	86.04
Transportation between M_2 and M_3	159	72.66
Factory 3	160.19	72.43
Transportation between M_3 and C	165.35	71.54

The overall service level rate for the SCN is 71.54%, as shown in Table 4.3. This means that the SCN does not meet the required service level rate of 90%. Therefore, RDO is applied using equation (4.1), where the objective here is to reduce total cycle time, time delay, and uncertainties. The required service rates of each entity and the SCN are constraints of the optimized model. Table 4.4 presents the cycle times obtained at each iteration, whereas Table 4.5 presents the robust service level rate of each entity in the SCN.

TABLE 4.4

CASE ONE - OBJECTIVE VALUES OBTAINED AT EACH ITERATION

Iteration	Objective (hr/batch)	Iteration	Objective (hr/batch)	Iteration	Objective (hr/batch)
0	990	5	727.56	10	717.58
1	781.49	6	725.5	11	717.16
2	755.39	7	723.14	12	716.16
3	734.37	8	722		
4	728.22	9	719		

TABLE 4.5

ROBUST SERVICE LEVEL RATE OF EACH ENTITY IN THE SCN

SCN Member	Time Delay (hr/batch)	Service Level Rate (percentage)
Factory 1	20	96.98
Transportation between M_1 and M_2	28.28	95.72
Factory 2	30.34	95.41
Transportation between M_2 and M_3	42.31	93.60
Factory 3	48.27	92.70
Transportation between M_3 and C	58.37	91.17

By applying RDO, the required service level rate is achieved, and the total cycle time is minimized. From Table 4.4, it is clearly shown that total cycle time, time delay, and uncertainties associated with total cycle time delay decreased from 990 hours per batch in the first iteration to 716.16 hours per batch in the final iteration. Also, all constraints are achieved, as shown in Table 4.5. The highest service level is at factory 1 with 96.98%. In contrast, the lowest service level is 91.17% for transportation from the last factory to customers. Table 4.6 presents the robust service level rate of each level in the SCN. Figure 4.4 illustrates the case one robust service level rate of all levels in the SCN, whereas Figure 4.5 shows case one distributions of mean total cycle time.

TABLE 4.6

ROBUST SERVICE LEVEL RATE OF EACH LEVEL IN THE SCN

Supply Chain Level	Time Delay (hr/batch)	SCN Service Level Rate (percentage)
Level 1	20	96.98
Level 2	30.34	95.41
Level 3	48.27	92.70
Level 4	58.37	91.17

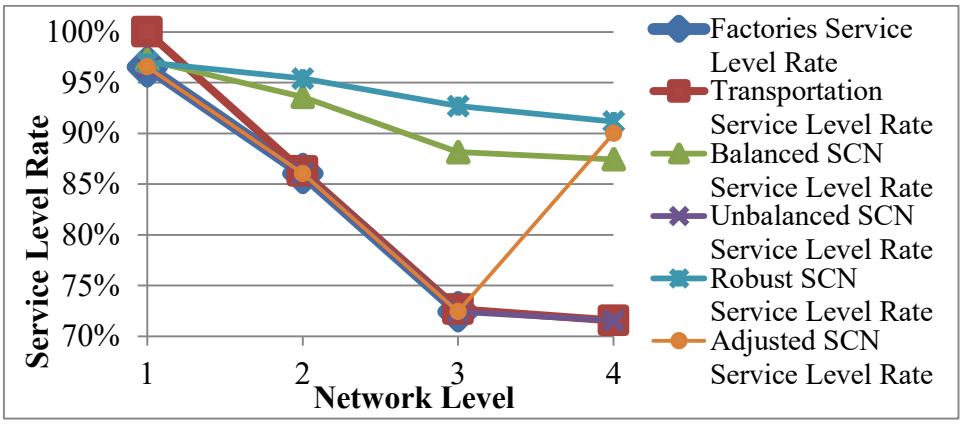

Figure 4.4. Robust service level rate of all levels

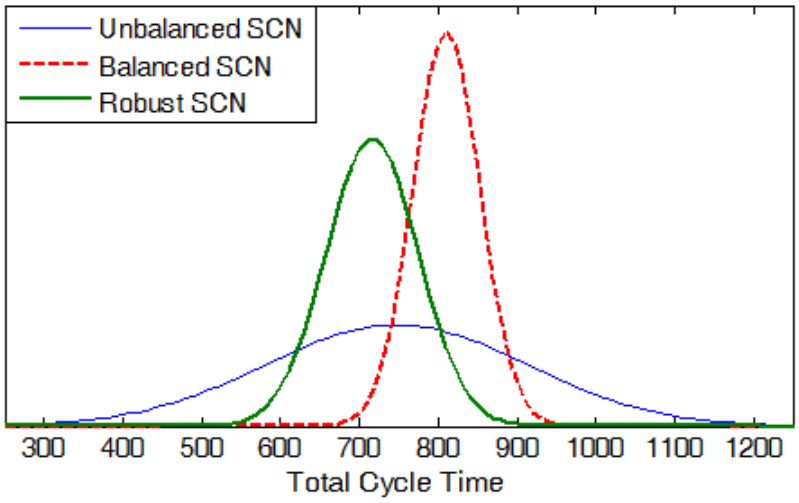

Figure 4.5. Distributions of mean total cycle time

By comparing RDO with previous strategies, it can be seen that there is less delay and faster cycle time. However, when comparing the balanced, unbalanced, and robust supply chain systems, it is clear that robust SCS has the lowest cycle time and meets the required service level rate. In fact, the balanced SCS holds less variation than the designed robust system, as shown in Figure 4.5, it but does not satisfy the required service level rate, as shown in Figure 4.4.

This optimization model determines the optimal service level rate value required at each entity in the SCS in order to satisfy the overall system service level rate. To enhance and satisfy

the required SL rate, additional resources should be added to the system. Adding resources such as machines, workers, and trucks help to satisfy the required SL rate but implies a higher cost as well. Using RDO has allowed for determining those entities that should be improved and the level of improvement that should be attained to satisfy the system's service level rate. In other words, improving the wrong manufacturing process or transportation method will cost time and money but will not help to satisfy the overall service level rate.

4.4.2 Case Study Two

The supply chain network in this case consists of connected parallel and series factories. This case study tests the efficacy of the methodology. This SCN consist of five levels and contains 22 entities. Figure 4.6 represents the complex supply chain system, where M_{ij} denotes factory i at level j, and $T_{(k,j-1)(i,j)}$ denotes transportation (route) from the previous factory k at level j-1 to factory i at level j. In this SCN, it is assumed that factories cannot start the required job until receiving all required parts from previous-level factories. For example, factory 4 ($M_{1,2}$) will not start until it receives the required parts from factory $M_{1,1}$ and factory $M_{2,1}$. For purposes of this case study, the collected data (design parameters) were assumed to be normally distributed, and their means and standard deviations are shown in Tables 4.7 and 4.8. To solve this case study, the SCS was modeled in MATLAB 2012a.

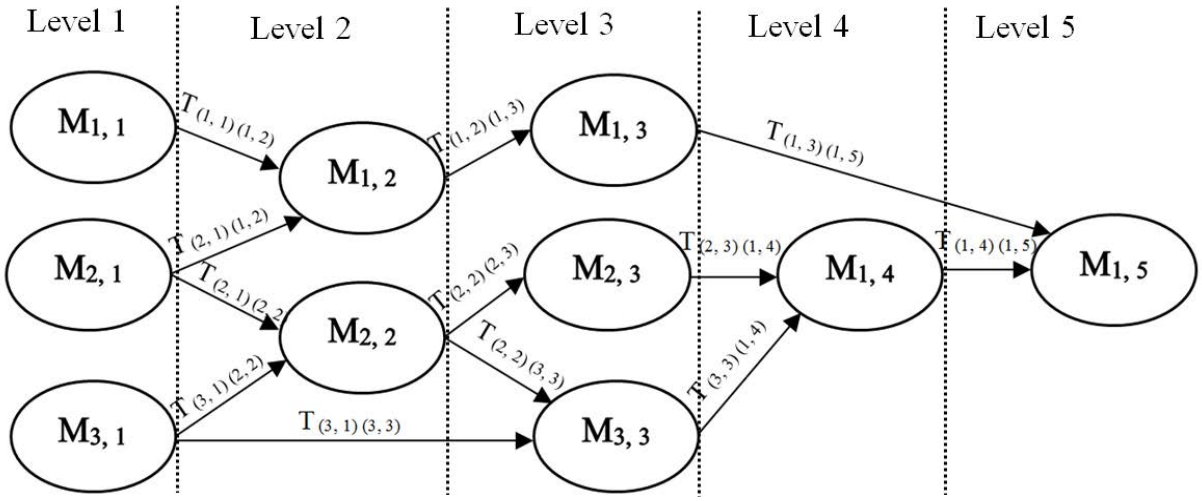

Figure 4.6. Case two - Schematic of complex SCN

TABLE 4.7

CASE TWO - FACTORY DESIGN PARAMETERS

SCN Factory	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Factory 1 ($M_{1,1}$)	85	20
Factory 2 ($M_{2,1}$)	79	11
Factory 3 ($M_{3,1}$)	91	15
Factory 4 ($M_{1,2}$)	83	13
Factory 5 ($M_{2,2}$)	80	17
Factory 6 ($M_{1,3}$)	85	22
Factory 7 ($M_{2,3}$)	88	18
Factory 8 ($M_{3,3}$)	77	21
Factory 9 ($M_{1,4}$)	90	15
Factory 10 ($M_{1,5}$)	76	19

TABLE 4.8

CASE TWO - TRANSPORTATION DESIGN PARAMETERS

SCN Route	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Route 1 ($T_{(1, 1)(1, 2)}$)	30	11
Route 2 ($T_{(2, 1)(1, 2)}$)	28	8
Route 3 ($T_{(2, 1)(2, 2)}$)	19	9
Route 4 ($T_{(3, 1)(2, 2)}$)	22	6
Route 5 ($T_{(3, 1)(3, 3)}$)	20	4
Route 6 ($T_{(1, 2)(1, 3)}$)	26	7
Route 7 ($T_{(2, 2)(2, 3)}$)	18	6
Route 8 ($T_{(2, 2)(3, 3)}$)	20	8
Route 9 ($T_{(1, 3)(1, 5)}$)	25	9
Route 10 ($T_{(2, 3)(1, 4)}$)	23	5
Route 11 ($T_{(3, 3)(1,4)}$)	20	10
Route 12 ($T_{(1, 4)(1, 5)}$)	17	7

First, the SCN mathematical model was implemented in MATLAB to measure the initial system performance. The procedures followed were similar to those used in case study one. Table 4.9 shows the computed service level rate for all factories when the SCN is unbalanced (current design). Table 4.10 provides the computed SL rate for transportation routes in the unbalanced SCN. Table 4.11 illustrates the overall SCN uncertainties and SL rates for each level in the unbalanced SCN.

TABLE 4.9

CASE TWO - INITIAL SERVICE LEVEL RATE OF FACTORIES IN SCN

SCN Factory	Time Delay (hr/batch)	Service Level Rate (percentage)
Factory 1 ($M_{1,1}$)	19	96.26
Factory 2 ($M_{2,1}$)	11.34	97.75
Factory 3 ($M_{3,1}$)	15.37	96.96
Factory 4($M_{1,2}$)	80	84.23
Factory 5 ($M_{2,2}$)	93	81.64
Factory 6 ($M_{1,3}$)	146.21	71.05
Factory 7 ($M_{2,3}$)	162.16	67.89
Factory 8 ($M_{3,3}$)	162.29	67.86
Factory 9 ($M_{1,4}$)	230.58	54.34
Factory 10 ($M_{1,5}$)	307.56	39.09

TABLE 4.10

CASE TWO - INITIAL SERVICE LEVEL RATE OF TRANSPORTATION IN SCN

SCN Route	Time Delay (hr/batch)	Service Level Rate (percentage)
Route 1 ($T_{(1, 1)(1, 2)}$)	76.10	84.93
Route 2 ($T_{(2, 1)(1, 2)}$)	65.13	87.10
Route 3 ($T_{(2, 1)(2, 2)}$)	75	85.18
Route 4 ($T_{(3, 1)(2, 2)}$)	86	82.98
Route 5 ($T_{(3, 1)(3, 3)}$)	87.04	82.76
Route 6 ($T_{(1, 2)(1, 3)}$)	137.37	72.79
Route 7 ($T_{(2, 2)(2, 3)}$)	155.53	69.20
Route 8 ($T_{(2, 2)(3, 3)}$)	154.34	69.44
Route 9 ($T_{(1, 3)(1, 5)}$)	207	59.02
Route 10 ($T_{(2, 3)(1, 4)}$)	227.04	55.04
Route 11 ($T_{(3, 3)(1,4)}$)	221	56.31
Route 12 ($T_{(1, 4)(1, 5)}$)	304	39.86

TABLE 4.11

CASE TWO - SERVICE LEVEL RATE OF EACH LEVEL

Supply Chain Level	Time Delay (hr/batch)	SCN Service Level Rate (percentage)
Level 1	19	96.26
Level 2	80	84.23
Level 3	162.29	67.86
Level 4	230.58	54.345
Level 5	307.56	39.09

As shown, the service level rate of the SCN decreases from the first level to the fifth level in the network. For example, in Table 4.11, the service level rate for level 1 is 96.26%, whereas in

level 2, the service level rate is decreased by 12.03% to 84.23%. This decrease is caused by different processing and transportation times between factories and associated uncertainties. The service level rate of the SCN is very low at 39.09%. In the next section, different scenarios are applied by balancing all transportation and processing times to analyze factors that have the highest impact on the service level of the SCN.

RDO was applied in order to reduce the total cycle time and also satisfy a 90% service level rate. MATLAB 2012a was used to model the SCN, and the same procedure as in the previous case study was followed. Table 4.12 shows the objective values in each iteration for the SCN cycle time. Table 4.13 indicates robust design variables for all factories in the SCN. Table 4.14 shows robust design variables to achieve the required SL rate for all routes in the SCN. Table 4.15 illustrates the SL rate for each level in the SCN after applying RDO. Figure 4.7 compares the distributions of mean total cycle time for unbalanced, balanced, and robust SCN designs.

TABLE 4.12

CASE TWO - OBJECTIVE VALUES OBTAINED AT EACH ITERATION

Iteration	Objective	Iteration	Objective	Iteration	Objective	Iteration	Objective
0	2260	3	822.759	6	821.926	9	820.746
1	824.249	4	822.543	7	821.506	10	820.427
2	823.773	5	822.034	8	821.25		

TABLE 4.13

ROBUST DESIGN VARIABLES FOR FACTORIES

SCN Factory	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Factory 1 ($M_{1,1}$)	86.21	20
Factory 2 ($M_{2,1}$)	81.06	11
Factory 3 ($M_{3,1}$)	92.18	15
Factory 4 ($M_{1,2}$)	83.79	13
Factory 5 ($M_{2,2}$)	81.59	17
Factory 6 ($M_{1,3}$)	86.19	22
Factory 7 ($M_{2,3}$)	88	18
Factory 8 ($M_{3,3}$)	80	21
Factory 9 ($M_{1,4}$)	90	15
Factory 10 ($M_{1,5}$)	80.62	19

TABLE 4.14

ROBUST DESIGN VARIABALE OF ROUTES

SCN Routes	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Route 1 ($T_{(1,1)(1,2)}$)	79.37	11
Route 2 ($T_{(2,1)(1,2)}$)	80.40	8
Route 3 ($T_{(2,1)(2,2)}$)	78.34	9
Route 4 ($T_{(3,1)(2,2)}$)	80.58	6
Route 5 ($T_{(3,1)(3,3)}$)	80.78	4
Route 6 ($T_{(1,2)(1,3)}$)	80.43	7
Route 7 ($T_{(2,2)(2,3)}$)	80.74	6
Route 8 ($T_{(2,2)(3,3)}$)	78.91	8
Route 9 ($T_{(1,3)(1,5)}$)	79.87	9
Route 10 ($T_{(2,3)(1,4)}$)	78.03	5
Route 11 ($T_{(3,3)(1,4)}$)	79.12	10
Route 12 ($T_{(1,4)(1,5)}$)	80.98	7

TABLE 4.15

ROBUST SERVICE LEVEL RATE FOR EACH LEVEL IN SCN

Supply Chain Levels	Time delay (hr/batch)	SCN Service Level Rate (percentage)
Level 1	15	98.03
Level 2	25	96.69
Level 3	47.22	93.72
Level 4	56.13	92.54
Level 5	69.14	90.81

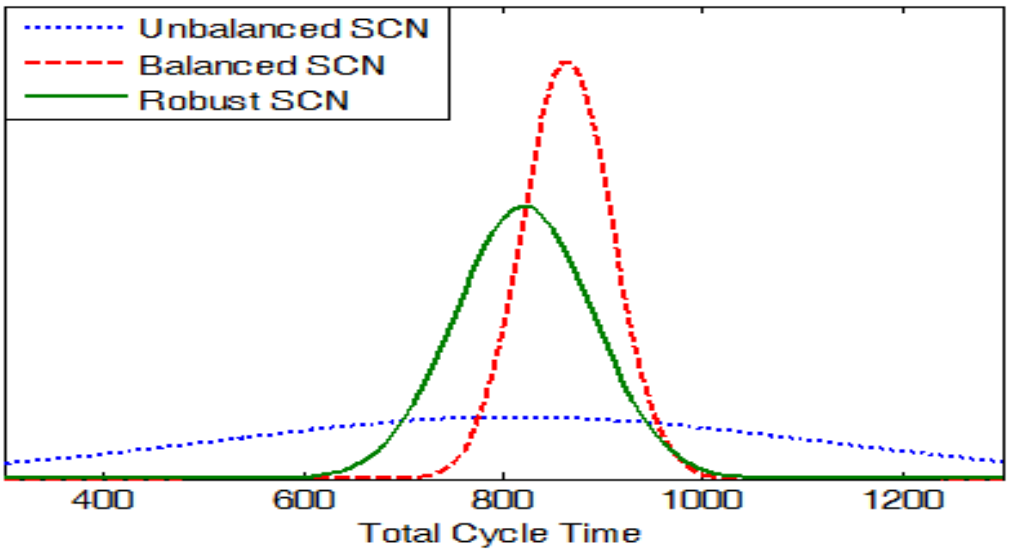

Figure 4.7. Case two - Distributions of mean total cycle time of SCN

By applying RDO, the required service level rate was achieved and total cycle time was minimized. From Table 4.12, it is clear that total cycle time, time delay, and uncertainties were decreased from 2,260 hours per batch in the first iteration to 820.427 hours per batch in the final iteration. Also, all constraints were achieved, as shown in Tables 4.13 and 4.14. In Table 4.15, the highest service level is at level one with 98.03%. In contrast, the lowest service level is 90.81% which represents the overall SCN service level rate. By comparing RDO with the balanced

strategy, it can be seen that the balanced SCN has a high service level rate and cycle time but less variation, as can be seen in Figure 4.7. However, when comparing the balanced, unbalanced, and robust SCNs, it is clear that the robust SCN has a low cycle time and satisfies the required service level rate.

4.5 Conclusion

This chapter focused on maintaining service level rates at each step in the factory supply chain. Also, it adds more value by using RDO in supply chain systems, which includes SCSs in which one factory supplies to another factory. This research studied the effects of uncertainty and delays introduced by production and transportation on the robustness of overall SCS performance. In summary, this study presented a novel robust design optimization methodology to derive designs of factory service level rates in order to satisfy the SL rate requirement of the system and ensure its robustness.

CHAPTER 5

EFFECT OF COST-EFFICIENT ROBUST GLOBAL SUPPLY CHAIN SYSTEM ON SERVICE LEVEL SATISFACTION

5.1 Introduction

A major tenet in a global supply chain system is to ensure continuous quality, reliability, resilience, and management improvement through strategic planning, operational tools, mathematical modeling, and optimization. This research studied global risk as well as uncertainty and service performance cost in the supply chain. It used robust design optimization to promote the objective of reducing service level cost, which is challenging due to the complexity of products, diversity of suppliers, geographic distribution of customers, and intertwined process among suppliers, manufacturers, distributors, retailers, and customer needs. From an SC management perspective, this set of synchronized decisions and actions is applied to efficiently integrate suppliers, manufacturers, transporters, retailers, and customers so that the right product is distributed to the right location at the right time, in the proper quantity, in an acceptable condition, and at the right price. However, global SC risks and uncertainty along with SL rate cost were studied in order to minimize the system-wide cost while maintaining customer satisfaction through SL requirements.

The objective of this chapter is to describe the details of a generic robust design optimization methodology to achieve overall system SL rate, minimize uncertainty impact, and minimize total performance cost. A cost-efficient robust supply chain system can be obtained by using RDO and considering all entities and activity in the SCS. This method will help to redesign an upstream SCS in which the system can be optimized to ensure SL rates and minimize performance cost, thus leading to improved production planning and higher profit. The rest of this

chapter/paper is organized as follows. Section 5.2 reviews the major tenets in logistic service level and SL cost in the global SCS. In Section 5.3 shows the development of a generic mathematical model for RDO of SCSs to ensure the required service level in complex systems while minimizing the system-wide cost. Section 5.4 discusses two case studies to illustrate and assess the effectiveness of the proposed approach. Finally, the chapter ends with a conclusion in section 5.5.

5.2 Supply Chain System and Quality Cost

In order to minimize manufacturing, service, and performance costs, an effective design of the global supply chain is necessary. In recent years, various manufacturers have implemented global supply chain systems to ensure the timely availability of material and labor resources while reducing inventory and improving production flexibility. The integration of supplier quality management, such as maintaining the service level requirement is significant for SC performance (Kaynak & Hartley, 2008). Some researchers have studied incentive schemes that induce reliable information in supply chains (Chiadamrong & Prasertwattana, 2006). Others have studied the implementation of quantity-based fixed incentives to organize inventory decisions in a decentralized SC. Some focus on the effect of SC relationships to quality performance. The focus of this research is satisfaction of the overall service level rate while minimizing service quality cost.

Supply chain quality management and SC management are both about developing a sense of SC community. Supply chain management is focused on building SC capabilities through tailored quality management practices (Madu et al., 2002). In the early 2000s, some researchers defined SC quality management as the formal coordination and integration of all partner organizations in the SC channel (Robinson & Malhotra, 2005). The common objective of both SC quality management and SC management is to develop a supply chain with achieved satisfaction

of internal and external customers. For example, Kuei et al. (2008) illustrated that modern business enterprises with supply chains need to scheme quality into SCs, optimize the flow of materials, stabilize the SC, and maximize the seamless sharing of data via an enterprise resource planning system. In this research, RDO was developed considering the minimization of processing and transportation uncertainty, delay, and variability along with service level cost in order to minimize the system-wide cost and satisfy the overall SL requirement.

Traditional supply chain system research problems consist of one supplier, a route, and depots. But in reality, a SCS can be more complicated than this, as shown in Figure 5.1. Most previous SCS research has focused on a single factory or production system that supplies products to multiple retailers. A logistic service level and performance cost of an upstream SC in which several manufacturers, either in parallel or in series, supplies to the final manufacturer, promotes a different set of constraints and issues. In Figure 5.1, $F_{i,j}$ represents factory i in level j, F_f is the final factory in the system, and i, j, and n are the total number of factories, levels, and customers respectively.

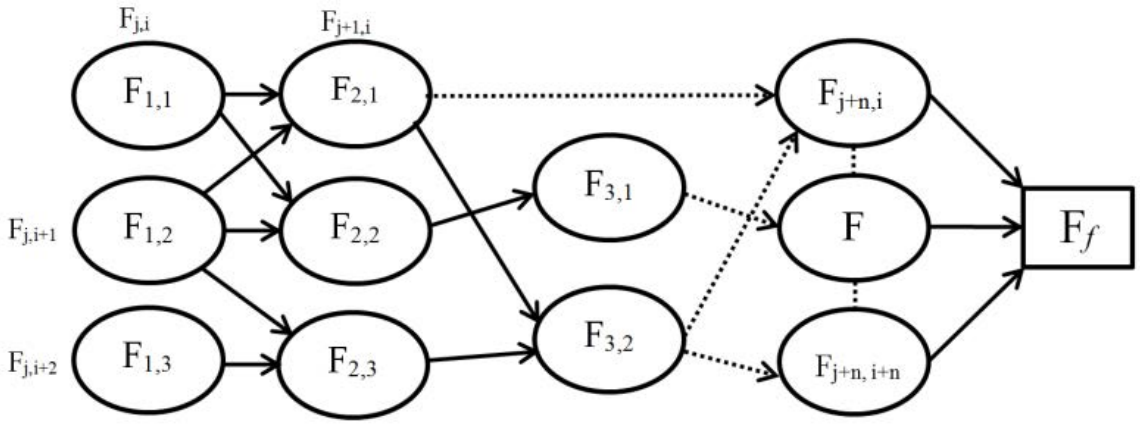

Figure 5.1. Typical upstream complex supply chain system

5.3 Robust Design Optimization and Generic Mathematical Model

Despite ample studies that consider robustness and uncertainty in a supply chain system design, to the best of this author's knowledge, none of the previous research has used RDO to minimize service level cost and simultaneously satisfy required SL rates of individual entities in the system and the overall SCS. From the literature, it is clear that there is an urgent need to study this type of interaction and its impact on the overall SCS performance. The main goal of using RDO in a supply chain system is to design the system with inherent robustness at the lowest cost possible. A robust SCS can be obtained by implementing RDO considering all entities and activity in the system. In this research, a generic robust and cost-efficient complex SCS design was developed using RDO, as shown in equation (5.1). The objective of this model is to minimize the cost of performance, which consists of the cost of reducing processing and transportation time, and the cost of reducing delay and uncertainty in manufacturing and transportation. The model constraints are required service level rate, the bounds of processing and transportation time, and uncertainty.

Minimize

$$\sum_{j=1}^{J}\sum_{i=1}^{I}(C\mu_{i,j}+C\sigma_{i,j}) \qquad \begin{array}{l} j=1,2,...,J \\ i=1,2,...,I \end{array}$$

Subject to

$$\begin{aligned} & SL\psi_{i,j} \geq Q\psi_{i,j} \\ & SL\zeta_{i,j} \geq Q\zeta_{i,j} \\ & SSL \geq SQ \\ & \mu\psi_{i,j}^{L} \leq \mu\psi_{i,j} \leq \mu\psi_{i,j}^{U} \\ & \sigma\psi_{i,j}^{L} \leq \sigma\psi_{i,j} \leq \sigma\psi_{i,j}^{U} \\ & \mu\zeta_{i,j}^{L} \leq \mu\zeta_{i,j} \leq \mu\zeta_{i,j}^{U} \\ & \sigma\zeta_{i,j}^{L} \leq \sigma\zeta_{i,j} \leq \sigma\zeta_{i,j}^{U} \end{aligned} \tag{5.1}$$

where $C\mu_{i,j}$ is the cost function for maintaining processing and transportation SL of the ith entity on level j, $C\sigma_{i,j}$ is the cost function for reducing uncertainty to improve SL of the ith entity on level j, $\mu_{i,j}$ is the processing and transportation time, $SL\Psi_{i,j}$ is the factory SL rate, $SL\zeta_{i,j}$ is the route SL rate, $Q\Psi_{i,j}$ is the required factory SL rate, $Q\zeta_{i,j}$ is the required route SL rate, SSL is the overall system SL rate, SQ is the required overall system SL rate, $\mu\Psi^{L}_{i,j}$ and $\mu\Psi^{U}_{i,j}$ are lower and upper allowable processing CT time reductions, respectively, $\sigma\Psi^{L}_{i,j}$ and $\sigma\Psi^{U}_{i,j}$ are lower and upper allowable processing CT variation reductions, respectively, $\mu\zeta^{L}_{i,j}$ and $\mu\zeta^{U}_{i,j}$ are lower and upper allowable transporting CT time reductions, respectively, and $\sigma\zeta^{L}_{i,j}$ and $\sigma\zeta^{U}_{i,j}$ are lower and upper allowable transporting CT variation reductions, respectively.

5.4 Case Studies

In this section, the efficacy of the proposed methodology is demonstrated by addressing two case studies. The first is a supply chain system consisting of entities in series. The second is a complex SC system consisting of series and parallel routes and factories. Both of these cases are SC systems with unbalanced entities, which means each entity has different processing and transportation times. Then RDO is modeled and implemented using MATLAB 2012a in order to improve the system performance and reduce cost.

5.4.1 Case Study One

Case study one considers a company that operates five manufacturing plants worldwide across all major geographic markets, as shown in Figure 5.2. Here, factories are connected in series, where the production flow of processing material cannot be interrupted.

Figure 5.2. Physical map

The supply chain system for the company can be divided into five major levels (Figure 5.3). To illustrate, raw material is transported to factory F_1, and after further processing, products are transported to factory F_2 as well as factories F_3, F_4, and F_5. The mean time to process one batch and the variability associated with processing as well as transportation are provided in Table 5.1. Moreover, it is assumed that if there is a transportation delay between levels, the factory at the next level will wait until materials or products have arrived. Also, products cannot be shipped from one factory to the next until the required quantity for a batch is completed.

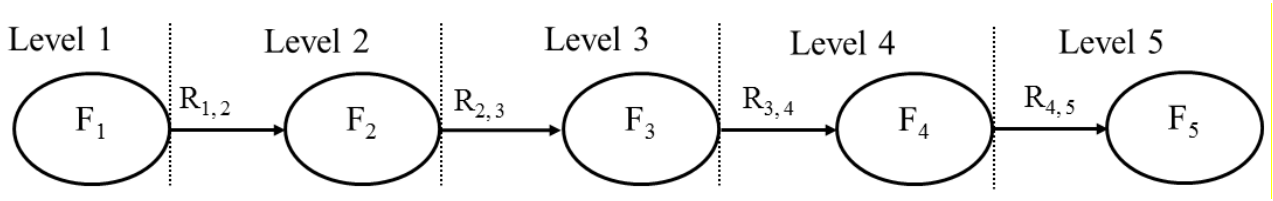

Figure 5.3. Schematic of supply chain system

TABLE 5.1

DESIGN PARAMETERS FOR CASE ONE

SC System Entity ($x_{i,j}$)	Mean Time (μ_{CT}) (hr/batch)	Time Variation (σ_{CT}) (hr/batch)
Factory 1 (F_1)	95	21
Factory 2 (F_2)	88	18
Factory 3 (F_3)	101	24
Factory 4 (F_4)	77	13
Factory 5 (F_5)	82	17
Route between F_1 and F_2 ($R_{1,2}$)	111	33
Route between F_2 and F_3 ($R_{2,3}$)	72	16
Route between F_3 and F_4 ($R_{3,4}$)	90	22
Route between F_4 and F_5 ($R_{4,5}$)	80	20

In the schematic of the supply chain system, there are nine entities which consist of five factories and four routes. In this case study, it is assumed that the cycle time of an entity cannot be reduced more than 30%. For example, in factory F_2, the improvement cycle time is 61.6 hr. This improvement can be computed as follows:

Improvement Cycle Time = 0% * Current Cycle Time

Each entity in this system has four performance cost functions: for processing time reduction, for increasing processing time, for variation reduction, and for increasing variation. These cost functions for all factories and routes, which are listed in Table 5.2, in practice can be determined from previous cost data.

TABLE 5.2

CASE ONE - COST FUNCTIONS

Entity ($x_{i,j}$)	Type	Minimizing Cost Function	Increasing Cost Function
F_1	$C\mu_{i,j}$	$y = -0.0024x^5 - 0.2412x^4 - 8.4072x^3 - 109.7x^2 - 616.37x + 116.36$	$y = 0.0006x^5 - 0.0603x^4 + 2.1x^3 - 27.42x^2 + 154.09x + 29.09$
	$C\sigma_{i,j}$	$y = -0.0000446x^6 - 0.00762x^5 - 0.4733x^4 - 13.24x^3 - 158.85x^2 - 820.32x - 220.71$	$y = 1.3x^2 + 25.84x + 61.62$
$R_{1,2}$	$C\mu_{i,j}$	$y = -0.0693x^3 - 2.9x^2 - 100x + 216$	$y = 0.5511x^2 + 11.838x + 189.19$
	$C\sigma_{i,j}$	$y = -0.0003x^5 - 0.023x^4 - 0.7x^3 - 8.76x^2 - 97.49x + 242.57$	$y = 0.0017x^4 - 0.118x^3 + 2.7632x^2 + 0.4118x + 158.89$
F_2	$C\mu_{i,j}$	$y = 0.0065x^5 + 0.6434x^4 + 21.99x^3 + 315.43x^2 + 1655.1x + 3184.4$	$y = -0.0031x^4 + 0.2465x^3 - 5.41x^2 + 59.87x + 58.19$
	$C\sigma_{i,j}$	$y = 10.61x^2 + 140.78x + 1405.4$	$y = 0.5385x^2 + 8.3878x + 144.02$
$R_{2,3}$	$C\mu_{i,j}$	$y = 1.78x^2 + 1.81x + 705.83$	$y = 1.09x^2 - 1.1x + 423.5$
	$C\sigma_{i,j}$	$y = 0.0042x^4 + 0.2513x^3 + 5.08x^2 - 6.45x + 489.21$	$y = 0.055x^3 - 2.42x^2 + 55.17x + 176.73$
F_3	$C\mu_{i,j}$	$y = 6.83x^2 + 35.32x + 1274.4$	$y = -0.0059x^4 + 0.4759x^3 - 10.23x^2 + 101.24x + 139.84$
	$C\sigma_{i,j}$	$y = 6.13x^2 + 31.72x + 1144.4$	$y = -0.0053x^4 + 0.4274x^3 - 9.24x^2 + 90.91x + 125.58$
$R_{3,4}$	$C\mu_{i,j}$	$y = -0.0202x^4 - 2.09x^3 - 56.18x^2 - 587.64x - 248.85$	$y = 0.3065x^3 - 8.5103x^2 + 122.29x + 483.97$
	$C\sigma_{i,j}$	$y = 19.20x^2 + 354.12x + 3006.2$	$y = 0.28x^3 - 7.64x^2 + 109.8x + 434$
F_4	$C\mu_{i,j}$	$y = 0.007x^5 + 0.6987x^4 + 24.01x^3 + 345.5x^2 + 1830x + 3165.4$	$y = 0.2039x^3 - 6.98x^2 + 86.89x - 13.5$
	$C\sigma_{i,j}$	$y = -0.8572x^3 - 29.17x^2 - 359.73x - 11.98$	$y = -0.0048x^4 + 0.6008x^3 - 17.56x^2 + 186.72x - 244.47$
$R_{4,5}$	$C\mu_{i,j}$	$y = 7.3523x^2 + 59.691x + 1142$	$y = 2.42x^2 - 19.69x + 376.87$
	$C\sigma_{i,j}$	$y = -0.0225x^4 - 1.88x^3 - 44.59x^2 - 445.16x - 113.95$	$y = -0.0094x^4 + 0.7866x^3 - 18.58x^2 + 185.56x - 47.49$
F_5	$C\mu_{i,j}$	$y = -0.0176x^4 - 2.237x^3 - 65.9x^2 - 711.26x - 281.45$	$y = -0.0016x^5 + 0.1579x^4 - 5.44x^3 + 78.53x^2 - 416.32x + 856.38$
	$C\sigma_{i,j}$	$y = -0.9492x^3 - 32.95x^2 - 420.96x + 647.15$	$y = 0.2088x^3 - 7.25x^2 + 92.61x + 142.37$

In general, a negative correlation exists between time and cost. For example, to improve processing activities in order to reduce cycle time, there is X amount of money that should be

invested to reduce the processing time by Y hours. Figure 5.4 illustrates the relation between cost and time reduction of factory three in the system.

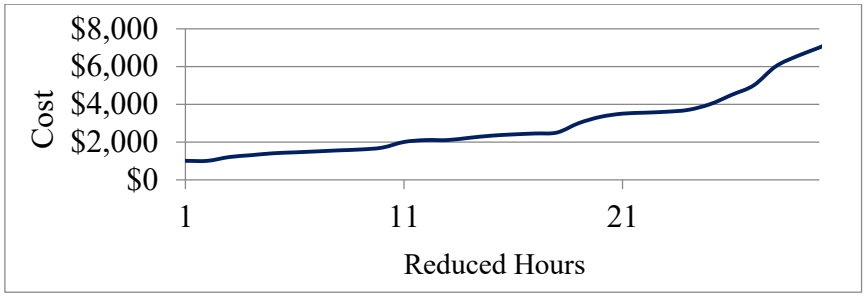

Figure 5.4. Cost of minimizing mean time of factory three

First, the proposed mathematical model was implemented in order to measure the initial system performance based on equations (3.2) to (3.6). The mathematical model was implemented in MATLAB. Using the MATLAB model, the cycle time for all entities in the supply chain was obtained. The total cycle time was then calculated by using a recursive equation (3.3). The expected delay for each entity in the SC was calculated next by using equations (3.5) and (3.6). Finally, the current service level rate was calculated.

Table 5.3 shows the current status of the SL system. Here, the first column consists of the SL system members, which are factories and routes that connect factories. The second column shows the measured mean cycle time in factories and routes to complete one batch. For example, the measured processing time in factory F_4 is 77 hours to complete one batch, and it takes approximately 80 hours on route $R_{(4, 5)}$ to arrive to the next factory F_5. The third column illustrates the current total cycle time, where at the beginning of the network, the cycle time equals zero. Then, processing in factory one takes around 116 hours, and after further process, it traverses to factories two, three, four, and five, respectively. For example, the cumulative cycle time at factory three takes around 618 hours, which can be computed by adding up the processing, transportation, and delay times (see equations [3.3] to [3.6]). The fourth column shows the variability in

processing and transportation times for each entity in the system. Column five represents the computed total delay for one batch at each entity in the system during processing and transportation. This cumulative delay $C_{\varepsilon i,j}$ is computed using equation (3.4). The last column shows the current SL rate of each entity in the system, which is computed using equation (3.2). From the SL rate results, it can be easily shown that the SL rate decreases during traveling from one point to the next in the system. For example, the SL of factory F_2 is 88.06%, whereas the SL rate in the next entity in the system (route between F_2 and F_3 ($R_{2,3}$)) is decreased by 4.02% to 84.045%.

TABLE 5.3

CASE ONE - INITIAL SUPPLY CHAIN SYSTEM STATUS

1	2	3	4	5	6
Entity ($x_{i,j}$)	**μ_{CT} (hr/batch)**	**μ_{TCT} (hr/batch)**	**σ_{CT} (hr/batch)**	***E* (hr/batch)**	***SL* (%)**
Factory 1 (F_1)	95	116	21	21	97.36
Route between F_1 and F_2 ($R_{1,2}$)	111	260	33	54	93.22
Factory 2 (F_2)	88	389	18	95	88.07
Route between F_2 and F_3 ($R_{2,3}$)	72	493	16	127	84.05
Factory 3 (F_3)	101	618	24	151	81.03
Route between F_3 and F_4 ($R_{3,4}$)	90	741	22	184	76.88
Factory 4 (F_4)	77	844	13	210	73.62
Route between F_4 and F_5 ($R_{4,5}$)	80	944	20	230	71.11
Factory 5 (F_5)	82	1,043	17	247	68.97

Next, the cost-efficient RDO is applied (model shown in equation [5.1]), where the objective is to reduce the SL rate cost for processing time, transportation time, and uncertainty. The required service rates of each entity and the SC system are constraints of the optimized model.

The proposed mathematical model was implemented to the SC system based on equations (3.2) to (3.6) and (5.1), and results of this optimization are shown in Table 5.4.

TABLE 5.4

CASE ONE - OBJECTIVE OPTIMAL SUPPLY CHAIN SYSTEM VALUES

1	2	3	4	5	6	7	8
Entity	μ_{CT} **(hr/batch)**	C_{μ} **($)**	σ_{CT} **(hr/batch)**	C_{σ} **($)**	μ_{TCT} **(hr/batch)**	ε **(hr/batch)**	***SL*** **(%)**
F_1	68	8,595	15	1,104	83	12.46	98.43
$R_{1,2}$	84.19	2,169	23.1	841	190	28.62	96.40
F_2	66.31	2,398	13	955	287	36	95.47
$R_{2,3}$	63	841	11.2	612	364.14	38	95.24
F_3	80.32	3,465	17	1,234	461.27	43.58	94.52
$R_{3,4}$	71	2,359	15.4	1,505	557	43.58	94.52
F_4	56	1,987	11	664	639	48.35	93.92
$R_{4,5}$	67	1,635	22	–262	728	62	92.21
F_5	67	2,219	19	–303	814	80	90

Table 5.4 shows the robust optimal values of the given SC system. The first column consists of SC system members, which are factories and routes that connect factories. The second column in the table shows the robust optimal mean cycle time for factories and routes to complete one batch. For example, the robust optimal processing time in factory F_3 should be 80.32 hours instead of 101 hours, and this improvement will cost $2,359 as shown in column three. Additionally, one batch of products should take 71 hours on route $R_{(3,4)}$ to arrive to the next factory F_4. Column four illustrates the robust optimal maximum variability that each entity should have in order to satisfy the design objective function and system SL requirement. For example, the robust optimal variability in the route between F_2 and F_3 ($R_{2,3}$) should not exceed 11.2 hours in order to satisfy quality cost and the SL rate. In the initial system status, the variability in route between F_2

and F_3 ($R_{2,3}$) was 16 hours, which does not satisfy system objective and constraint requirements. In order to reduce the variability in route F_2 and F_3 ($R_{2,3}$) by 4.8 hours from 16 to 11.2, the cost would be $612, as shown in column five in Table 5.4. The sixth column in Table 5.4 illustrates the robust optimal total cycle time that a batch takes to complete from the beginning of processing until the last member exits the system. For example, the total cycle time to complete one batch at factory F_4 should be 639 hours. The system robust optimal total cycle time to complete a batch that satisfies the SL requirement is 814 hours. In the initial SC system design, the total cycle time to complete one batch was 1,043 hours, as shown in Table 5.3, but that does not satisfy the SL rate requirement and results in 68.97%. In other words, by reducing the total cycle time by 229 hours, from 1,043 to 814 hours, an SL rate of 90% can be satisfied, and this will cost a total of $32,020.90, as shown below in Table 5.5. The amount of $32,020.90 resulted from the summation of all entities' robust optimal SL costs of processing time reduction (column three in Table 5.4) and the SL cost of uncertainty reduction (column five in Table 5.4) that resulted from the RDO.

TABLE 5.5

CASE ONE - OBJECTIVE VALUES OF SOME ITERATIONS

Iteration	f(x)	Iteration	f(x)	Iteration	f(x)	Iteration	f(x)
1	–1.66E + 17	160	34,133.1	468	32,144	488	32,020.9
2	1.90E + 13	161	34,081.1	469	32,143.9	489	32,020.9
3	1.90E + 13	162	34,069.8	470	32,143.8	490	32,020.9
4	–8.28E + 19	163	34,002	471	32,143.6	491	32,020.9
5	–3.28E + 15	164	33,951.9	472	32,143	492	32,020.9

By applying the developed RDO model, the required SL rate is achieved, and the total SL cost is minimized, as shown in Table 5.5. From Table 5.5, the minimum total quality cost of processing time and uncertainty is achieved after 492 iterations at a cost of $32,020.90.

In some situations, the quality costs shown in Table 5.4 are negative values, which means that the system saved money. For example, as shown in column five of Table 5.4, the variability in reduction costs at factory F_5 is $–303. This negative value indicates that the system saved $303, because processing variability at factory F_5 was increased by 2 hours (from 17 to 19 hours), which saved money. Improving or reducing cycle time can be controlled by adding or reducing workers, cars, machines, tools, etc. Improving or reducing variability can be controlled by having trained employees and efficient machines. The last column in Table 5.4 (column eight) shows the robust optimal SL rate values of each entity in the system in order to satisfy the overall system SL rate of 90%. Figure 5.5 illustrates the initial and robust optimal SL rate of the given SC system.

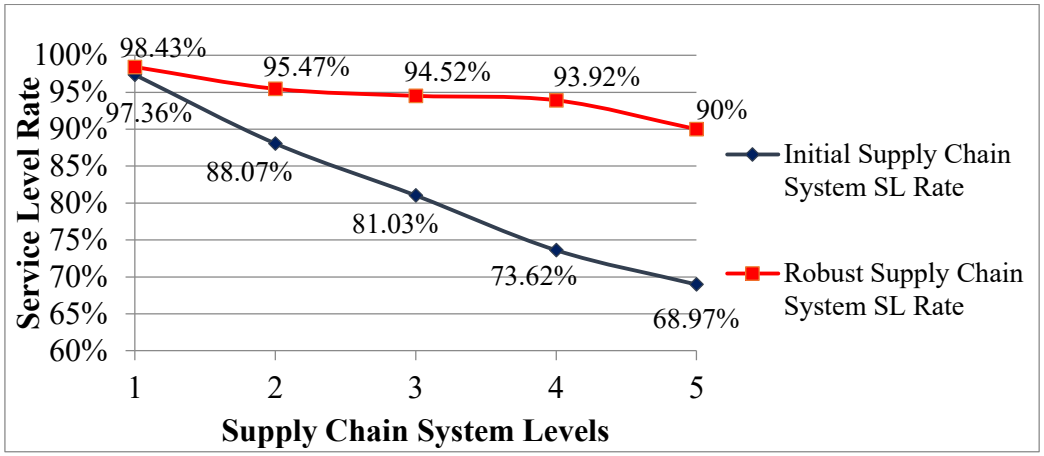

Figure 5.5. Case one - Service level rate for all levels

In general, the service level rate of supply chain systems decreased monotonically when traversing from the input point to the output point (sink) in the system. This resulted in the negative correlation between the SL rates with SC levels. For example, the initial design SL rate on level one is 97.36%, whereas in level two, the SL rate decreased by 9.29% to 88.07%, due to the differences in processing times between factories and uncertainties associated with processing and transportation time. The overall SL rate for the initial SC system was 68.97% and did not meet the required SL rate of 90%. However, by applying the developed RDO model, the required SL rate

of 90% was achieved, as shown in Figure 5.5 and Table 5.4. Figure 5.6 describes the distributions of initial and robust SC system cycle times.

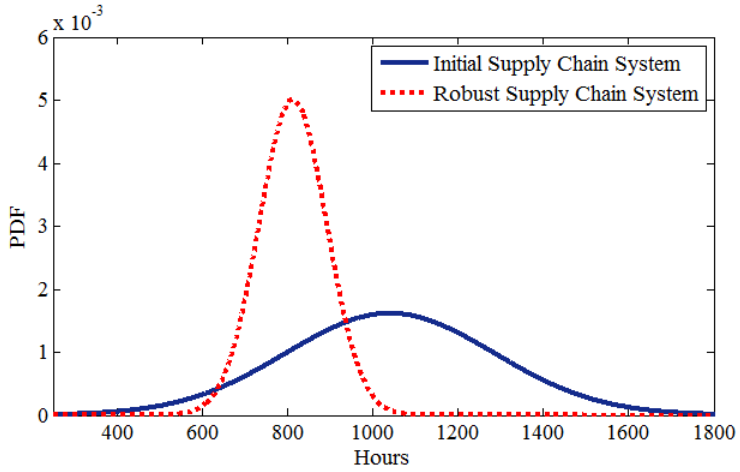

Figure 5.6. Distributions of mean total cycle time

In studying the distributions of mean cycle time of RDO design and initial SC system design, the time variation is significantly reduced because the total delays in the system were reduced by 167 hours from 247 to 80 hours. Moreover, the RDO resulted in a lower mean cycle time. Also, the SC system's cycle time was reduced by 229 hours, from 1,043 to 814 hours. When comparing initial system design with robust system design, it is clear that robust system design has faster cycle times and lower variation, and meets the required SL rate of 90%. Also, the proposed model was run for the given case, but the SL rate requirements were reduced to 80% instead of 90%. Results show that the total cost to improve the system SL rate from 68.97% to 80% would cost $17,704.5. Furthermore, the proposed model was run for the given case with a higher SL rate of 97% instead of 90%. Results show that the total quality cost to improve the system SL rate from 68.97% to 97% cost $39,644.9. In summary, to improve the system SL rate from 68.97% to 80% will cost $17,704.5, to improve the system SL rate from 68.97% to 90% will cost $32,020.9, and to improve the system SL rate from 68.97% to 97% will cost $39,644.9. Figure 5.7 presents the distributions of total cycle time for SL rates of 68.97%, 80%, 90%, and 97%. Therefore, it can be

concluded that by increasing the required SL rate, the SL cost will increase. Also, from Figure 5.7, it can be seen that by increasing the SL rate, the system's variation and cycle time decreases.

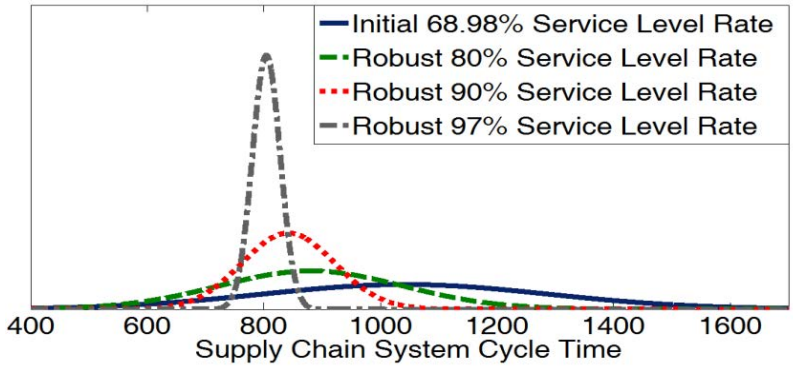

Figure 5.7. Distribution of mean total cycle time for different service level rates

This case study tested the effectiveness of the proposed model and techniques, emphasizing that by applying the proposed RDO model to any series SC system, the required SL rate can be achieved while the SL cost and uncertainty are minimized. In the following subsection, the developed cost-efficient RDO methodology for the SC system is applied to a complex SC system consisting of multiple factories and routes that are connected in series and parallel.

5.4.2 Case Study Two

This case demonstrates the efficacy of the developed RDO approach in redesigning complex SC systems consisting of connected parallel and series factories. This system consists of 5 levels and contains 19 entities; the entities are 9 factories and 10 routes as shown in Figure 5.8.

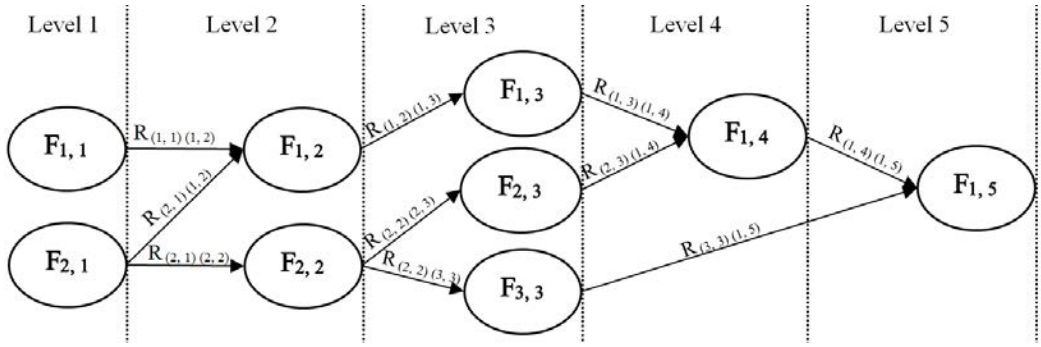

Figure 5.8. Schematic of complex supply chain system

In this SC system, factories cannot start the required job until they have received all required parts from previous-level factories. For example factory $F_{1,4}$ will not start until it receives the required parts from factory $F_{1,3}$ and factory $F_{2,3}$. Also, maximum improvement of cycle time is limited and cannot be more than 20%. As in case one, each entity in this SC system has four cost functions for processing time reduction, for increasing processing time, for variation reduction, and for increasing variation. This means that this case study has a total of 76 cost functions. For the purpose of this case study, the collected data (design parameters) were assumed to be normally distributed, and their means and standard deviations are shown in Table 5.6. To solve this case study, RDO was modeled based on this case and implemented in MATLAB 2012a.

Using the MATLAB model, the cycle times for all entities in the supply chain were obtained. The total cycle time was then be calculated by using the recursive equation (3.3). The expected delay for each entity in the SC was calculated next by using equations (3.5) to (3.6). Next, the current SL rate was evaluated using equation (3.2). Then, RDO was applied in order to minimize the performance cost of reducing processing and transportation times, and performance cost of reducing the associated uncertainty using equation (5.1). Next, the analysis results analysis can be concluded. Table 5.7 shows the initial processing and transportation performance that illustrates mean cycle time on each factory, system cycle time, variability, system delay, and current service level. Table 5.8 shows robust optimal processing and transportation values that include mean cycle time, system cycle time, variability, system delay, current SL optimal cost of processing time reduction and optimal cost of uncertainty reduction. Table 5.9 shows the objective value for some iteration during RDO for the supply chain system total quality cost.

TABLE 5.6

FACTORY AND ROUTE DESIGN PARAMETERS FOR CASE TWO

SCS Entity ($x_{i,j}$)	**Mean Time (μ_{CT}) (hr/batch)**	**Time Variation (σ_{CT}) (hr/batch)**
Factory 1 ($F_{1,1}$)	195	46
Factory 2 ($F_{2,1}$)	181	25
Factory 3 ($F_{1,2}$)	209	34
Factory 4($F_{2,2}$)	190	29
Factory 5 ($F_{1,3}$)	184	39
Factory 6 ($F_{2,3}$)	195	50
Factory 7 ($F_{3,3}$)	202	41
Factory 8 ($F_{1,4}$)	177	48
Factory 9 ($F_{1,5}$)	207	34
Route 1 ($R_{(1,1)(1,2)}$)	173	41
Route 2 ($R_{(2,1)(1,2)}$)	142	19
Route 3 ($R_{(2,1)(2,2)}$)	163	27
Route 4 ($R_{(1,2)(1,3)}$)	149	23
Route 5 ($R_{(2,2)(2,3)}$)	144	30
Route 6 ($R_{(2,2)(3,3)}$)	133	39
Route 7 ($R_{(1,3)(1,4)}$)	158	32
Route 8 ($R_{(2,3)(1,4)}$)	138	37
Route 9 ($R_{(3,3)(1,5)}$)	168	22
Route 10 ($R_{(1,4)(1,5)}$)	153	36

TABLE 5.7

INITIAL SUPPLY CHAIN SYSTEM FACTORY STATUS

1	2	3	4	5	6
SCS Entity ($x_{i,j}$)	**μ_{CT} (hr/batch)**	**μ_{TCT} (hr/batch)**	**σ_{CT} (hr/batch)**	**ε (hr/batch)**	***SL* (%)**
Factory 1 ($F_{1,1}$)	195	241	46	46	97.13
Factory 2 ($F_{2,1}$)	181	206	25	25	98.44
Factory 3 ($F_{1,2}$)	209	720	34	143	91.09
Factory 4 ($F_{2,2}$)	190	633	29	99	93.83
Factory 5 ($F_{1,3}$)	184	1,175	39	265	83.49
Factory 6 ($F_{2,3}$)	195	1,109	50	236	85.30
Factory 7 ($F_{3,3}$)	202	1,048	41	179	88.85
Factory 8 ($F_{1,4}$)	177	1616	48	371	76.88
Factory 9 ($F_{1,5}$)	207	2,070	34	465	71.03
Route 1 ($R_{(1,1)(1,2)}$)	173	477	41	109	93.21
Route 2 ($R_{(2,1)(1,2)}$)	142	406	19	83	94.83
Route 3 ($R_{(2,1)(2,2)}$)	163	414	27	70	95.64
Route 4 ($R_{(1,2)(1,3)}$)	149	952	23	226	85.92
Route 5 ($R_{(2,2)(2,3)}$)	144	864	30	186	88.41
Route 6 ($R_{(2,2)(3,3)}$)	133	805	39	138	91.40
Route 7 ($R_{(1,3)(1,4)}$)	158	1,391	32	323	79.88
Route 8 ($R_{(2,3)(1,4)}$)	138	1,341	37	330	79.44
Route 9 ($R_{(3,3)(1,5)}$)	173	1,272	22	235	85.36
Route 10 ($R_{(1,4)(1,5)}$)	142	1,829	36	431	73.15

Table 5.7 shows the current status of factories and routes in the SC system. The first column in the table shows the factories and routes in the system and their locations. For example, $F_{2,3}$ is factory number two in level three, and $R_{(2,2)(2,3)}$ is the route that connects factory $F_{2,2}$ with factory $F_{2,3}$. The second column in the table shows the initial mean cycle time in factories during

processing and routes during transportation to complete one batch. For example, the measured processing time to complete one batch in factory 7 ($F_{3,3}$) is 202 hours. The third column in Table 5.7 illustrates the current total cycle time that one batch takes to complete from the beginning of the processing until the last one exits the entity, which can be calculated using equation (3.3). For example, one batch will take 1,109 hours until it exits factory $F_{2,3}$. The fourth column shows the initial processing time and transportation variability for each factory in the system. Column five describes the calculated system delay for completing one batch for each entity, and that is calculated by using equation (3.4). The last column six shows the current SL rate at each factory and route. This is calculated by using equation (3.2). For example, the initial SL rate at factory 8 ($F_{1,4}$) is 76.88%.

Next, RDO was applied using the developed optimization model shown in equation (5.1), where the objective was to minimize SL cost for processing time, transportation time, and uncertainty, simultaneously. The required service rates for each entity in the system and required overall service rate for the SC system are constraints of the optimized model; results of this optimization are shown in Table 5.8. The first column in this table consists of the SC system entities, which are factories and the routes that connect those factories. The second column shows the robust optimal mean cycle time for factories and routes to complete one batch. For example, the robust optimal processing time in factory $F_{2,2}$ should be 152 hours instead of 190 hours as in the initial design, and this improvement will cost $3,661, as shown in column three. And, it should take 115.2 hours on the route $R_{(2,2)\,(2,3)}$ to arrive at the next factory, whereas in the initial design from Table 7, one batch takes 144 hours on route $R_{(2,2)\,(2,3)}$.

In some situations, SL costs (columns three and five, Table 5.8) are negative values, meaning there is a savings on resources (money). For example, in Table 5.8, column three shows

the SL cost of transportation time reduction on $R_{(2,1)(1,2)}$ is \$-650. This negative value indicates there is a savings of \$650, because transportation time on $R_{(2,1)(1,2)}$ was increased by 14 hours, from 142 to 156 hours, thus saving money. Improving or reducing cycle time can be controlled by adding or reducing workers, cars, machines, tools, etc.

TABLE 5.8

OBJECTIVE OPTIMAL SUPPLY CHAIN SYSTEM VALUES

1	2	3	4	5	6	7	8
Entity	μ_{CT} **(hr/batch)**	C_{μ} **(\$)**	σ_{CT} **(hr/batch)**	C_{σ} **(\$)**	μ_{TCT} **(hr/batch)**	ε **(hr/batch)**	***SL*** **(%)**
$F_{1,1}$	156	8,268	37	1,628	193	2.2	99.86
$F_{2,1}$	156	5991	24	–21	181	2.2	99.86
$F_{1,2}$	167.2	10,359	30	15,961	579	4	99.75
$F_{2,2}$	152	3,661	23.25	689	515	23.37	98.54
$F_{1,3}$	147.2	3,787	31.2	1,619	943	56.15	96.5
$F_{2,3}$	156	2,919	40	1,285	873	56.15	96.5
$F_{3,3}$	162	2,925	33	1,029	869	56.15	96.5
$F_{1,4}$	142	6,204	38.4	1,468	1,295.5	107	93.35
$F_{1,5}$	166	7,082	27.2	1,646	1,659	160.5	90
$R_{(1,1)(1,2)}$	156	4,169	32.8	2,948	381.6	174.1	89.13
$R_{(2,1)(1,2)}$	156	–650	23.4	–190	360.37	211.4	86.82
$R_{(2,1)(2,2)}$	130.4	1,207	28	–84	365	232.4	85.52
$R_{(1,2)(1,3)}$	147.12	878	18.4	1,205	764.37	271	83.13
$R_{(2,2)(2,3)}$	115.2	5,485	24	1,095	677	272	83.06
$R_{(2,2)(3,3)}$	129	2,022	31.2	1,414	675	279	82.59
$R_{(1,3)(1,4)}$	141.5	2,908	26	1,557	1,116	327	79.62
$R_{(2,3)(1,4)}$	205.4	–3,500	39.54	–169	1,118	434	72.96
$R_{(3,3)(1,5)}$	252	–178,134	33	–368	1,154	551	65.67
$R_{(1,4)(1,5)}$	142	2,835	29	2,042	1,466	619	61.43

Robust optimal maximum variability that each entity should have in order to satisfy the design objective function and system service level requirement are shown in column four in Table 5.8. For example, the robust optimal variability for factory $F_{1,3}$ should not exceed 31.2 hours in order to meet SL rate requirements. In the initial system design, variability of factory $F_{1,3}$ was 39 hours, which does not satisfy system objective and constraint requirements. In order to reduce the variability on factory $F_{1,3}$ by 7.8 hours, from 39 hours to 31.2 hours, the cost is $1,619, as shown in column five.

The sixth column in Table 5.8 illustrates robust optimal system cycle time that one batch takes to complete from the beginning of the processing until the last product exits the system, which is factory $F_{1,5}$. The robust optimal system cycle time to complete one batch that satisfies the SL requirement is 1,646 hours. In the initial design, the total cycle time to complete one batch was 2,070 hours, as shown previously in Table 5.7, but that does not satisfy the SL rate requirement and therefore results in a 71.03% SL rate. On the other hand, when reducing the total cycle time by 424 hours, from 2,070 hours to 1,646 hours, the SL rate of 90% can be satisfied. Column seven shows cumulative delay in the system, and the total delay for this SC system design is 160.5 hours, whereas it was 465 hours in the original design. The last column in Table 5.8 shows robust optimal service level rate values that each entity in the system should have in order to satisfy the overall system SL rate of 90%.

Figure 5.9 illustrates the initial and robust optimal SL rate of the given SC system. In general, the SC system SL rate decreases monotonically when traversing from the input point to the output point within the system. Also, there is a negative correlation between SL rates and SC levels. For example, on the optimal robust design, SL rate on level one is 99.86%, whereas in level three, the SL rate decreased by 6.51% to 93.35% due to differences in processing and

transportation times between factories and routes and uncertainties associated with both. The overall SL rate for the initial design of the SC system was 71.03%, but by applying the developed RDO approach, the required SL rate of 90% was achieved, as shown in Figure 5.9.

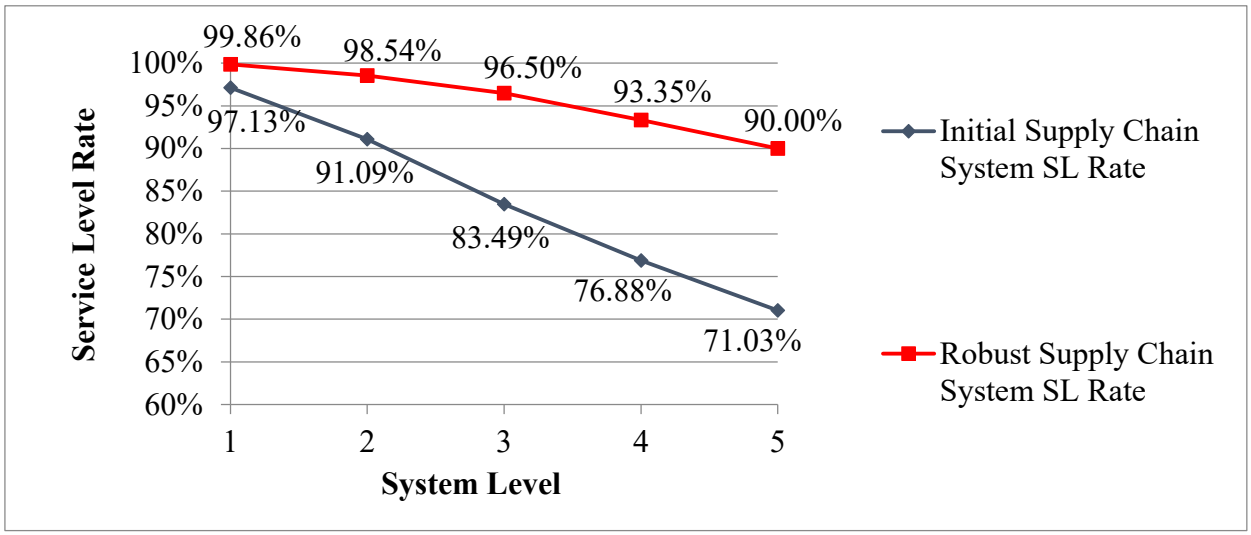

Figure 5.9. Service level rates for all system levels

Table 5.9 shows histories of the objective value function for some iterations, which is the sum of the four performance cost functions (for processing time reduction, for increasing processing time, for variation reduction, and for increasing variation). By applying this developed RDO approach, required SL rate is achieved, and total performance cost is minimized. From Table 9, the minimum total performance cost is achieved after 1654 iterations with a total savings of $76,927.70. In summary, the developed RDO not only assured the required SL rate of 90%, but was also able to save money by efficiently redesigning the SL rate values of each entity in the system.

TABLE 5.9

OBJECTIVE VALUES IN EACH ITERATION

Iteration	f(x)	Iteration	f(x)	Iteration	f(x)	Iteration	f(x)
1	120,818	414	–75,314.3	1,162	–74,137.4	1,648	–76,927.3
2	203,010	415	–76,649.7	1,163	–75,359	1,649	–76,927.5
3	–1.21E + 06	416	–61,039	1,164	–75,578.8	1,650	–76,927.6
4	–1.33E + 06	417	–60,879.1	1,165	–75,626.2	1,651	–76,927.6
5	–47,684.7	418	–74,941.6	1,166	–75,623.4	1,652	–76,927.6
6	–31,974.6	419	–75,013.9	1,167	–75,630.3	1,653	–76,927.6
7	–65,650.3	420	–76,766.3	1,168	–75,631.2	1,654	–76,927.7

Figure 5.10 describes distributions of both initial and robust supply chain system cycle times. By comparing distributions of the mean cycle time of RDO design and initial SCS design, the time variation is significantly reduced because the total delay in the system was reduced by 307 hours, from 465 hours to 160.50 hours. Moreover, the RDO resulted in a lower mean cycle time where the mean cycle time of the SCS is reduced by 424 hours from 2,070 hours to 1,646 hours. When comparing initial system design and developed RDO, it is clear that robust system design has faster cycle time and lower variation, and satisfies the required service level rate.

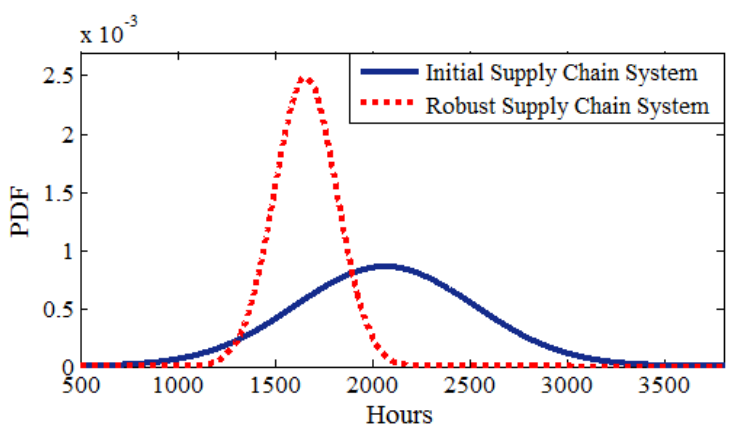

Figure 5.10. Distributions of mean total cycle time

This case study is different from case study one since the supply chain investigated is much more complex and has more entities. After analyzing case two, it was found that there are more chances of saving costs since there are many entities to be redesigned. Also, in this case study, the required SL rate of 90% is satisfied, and the optimization resulted in a savings of $76,927.7. By redesigning the SCS using the develop RDO approach, it was possible to identify which factories and routes in the system had processing or transportation times that should be reduced or increased in order to save costs. Furthermore, these changes would not affect the overall supply chain service level rate. This research also showed which entity needs more improvement to satisfy the SL rate. Also, the newly developed RDO approach was able to balance between performance cost and SL rate of all entities in the system in order to minimize the system-wide cost and satisfy the overall system's SL rate requirement.

5.5 Conclusion

After reviewing the current literature relative to supply chain system quality costs, global SC measures, logistic service qualities in the global SCS, supply chain management, and RDO, it was possible to develop a generic RDO model for global SCSs. This chapter used the approach in Chapter 3 for evaluating the SCSs using service level as a measure of effectiveness. Other measures that are typically used for measuring an SCS are fill rate, confirmed fill rate, response delay, and available stock. However, under uncertainty conditions, it was found that SL is a much better performance metric to ensure that delays do not occur within the SCS. A novel method of designing SCSs using RDO that minimizes uncertainty and reduces costs was also detailed. This approach of designing SCSs helps to identify the factory or the route that should be improved to minimize cost while ensuring service level rate requirements.

Case studies on the use and effectiveness of the modeling techniques that were developed were also provided. Results and analysis of this research emphasize that the proposed model can be used to redesign an upstream supply chain system where the system can be optimized to ensure SL rates, which will lead to improved SC design planning and reduced costs. This research addresses the need of developing a methodology to design a cost-efficient SCS with the ability to highlight which factory and/or route in the system should be improved and how much this improvement will cost to satisfy overall SL rate requirements.

In this chapter, it was possible to complete the third research thrust and address the research question on developing a methodology to design a cost-efficient supply chain system able to highlight which factory in the system should be improved and how much this improvement will cost to satisfy the service level rate.

CHAPTER 6

MEASUREMENT AND OPTIMIZATION OF RELIABILITY IN COMPLEX SUPPLY CHAIN SYSTEMS

6.1 Introduction

With trade deregulation and globalization, supply chains have become increasingly global and complex. Supply chain systems have emerged as the new frontier for generating competitive advantages. It is now no longer a given single business competing against another; instead, it is the entire supply chain system competing against other supply chain systems in the global market. Because of uncertainties induced by various sources such as transportation delay and manufacturing process variability, ensuring the reliability of the overall SCS and all members in the system while considering these uncertainties is a highly complex task. This chapter introduces a novel measure to quantify the reliability rate of the overall SCS and the reliability of each member involved in the system. Also introduced here is an optimization approach to develop the reliability of each entity in the SCS such that the reliability rate requirement is ensured for the overall system. Methodology, numerical examples, and case studies are provided to illustrate the approaches for calculating the SCS reliability rate. These case studies include simple ones as well as a multi-level complex SCS.

6.2 Model for Measuring Supply Chain System Reliability

In this section, the developed supply chain system reliability measure is explained and detailed using a numerical example. Consider the case of a company that manufactures different types of products and purchases its parts from a supplier that could be another manufacturing plant. Supplier S_i can supply up to x number of the demand p for factory F_i (Figure 6.1) to produce product z. Supplier S_i spends t_i time to produce x number of the demand p for factory F_i. And

factory F_i spends time t_i to complete the production of the required product z, where the company spends a total of T_i time to produce product z. Also, the company must manufacture the product z by the due date T^T.

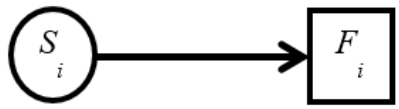

Figure 6.1. Typical upstream supply chain system

This interaction between the supplier and the factory can be expressed mathematically as $x = p$, where the output x of supplier S_i must be equal to the quantity p that factory F_i ordered to produce product z. And T_i is the total time that the company spent to manufacture product z. The reliability rate (Ω) can be statistically expressed as the probability of producing product z before the due time (T^T), as shown in equation (6.1).

$$\Omega = Pr(T_i \leq T^T) \tag{6.1}$$

Mathematically, the supply chain reliability rate of an entity in the SCS is calculated as

$$\begin{aligned}
&\Omega_{X(i,j)} = \left(T^T - \left(f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{X(i,j)}} + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{X(i,j)}} \right) \right) \times \frac{1}{T^T} \\
&when \qquad T^T \leq \left(f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{\mathrm{X}(i,j)}} + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{\mathrm{X}(i,j)}} \right), \ \Omega_{X(i,j)} = 0 \\
&where \\
&\varepsilon_{\mathrm{X}(i,j)} = \begin{cases} if \ f_{\mu\,\mathrm{X}(i,j-1)} > f_{\mu\,\mathrm{X}(i,j)} \ , \quad f_{\mu\,\mathrm{X}(i,j-1)} - f_{\mu\,\mathrm{X}(i,j)} \\ 0 \quad otherwise \end{cases}
\end{aligned} \tag{6.2}$$

where $\Omega_{X(i,j)}$ represents the reliability rate of entity type X number i in level number j to complete the required job, T^T represents the due time, and $\sigma_{X(i,j)}$ is the standard deviation (uncertainty) of entity distribution functions for type X number i in level number j . Krishnan et al. (2009) provided an example that shows how the convolutions of two distribution functions can be calculated, where

$\varepsilon_{i\ X(i,j)}$ is the delay waiting time that type X number i in level number j spent waiting for products from a previous entity type X number i at level number j-1, and $\mu_{X(i,j)}$ is the mean time to complete a required job at entity type X number i in level number j . When the sum of the delay ($\varepsilon_{X(i,j)}$) and uncertainty ($\sigma_{X(i,j)}$) are longer than the due time (T^T), the reliability rate ($\Omega_{X(i,j)}$) is equal zero, where X represents the type of entity, which can be either the route (R), factory (F), or supplier (S), i represents the entity number, and j represents the level number.

6.2.1 Numerical Example

This example consists of a supply chain system that has two levels and three entities, as shown in Figure 6.2. These entities are supplier ($S_{1,1} = N(30,3^2)$), route ($R_{2,1} = N(25,4^2)$), and factory ($F_{2,1} = N(32,3^2)$). The due date to complete one batch is 80 hours ($T^T = 80$). The objective of this example is to demonstrate the measurement of the system reliability rate using the developed measure.

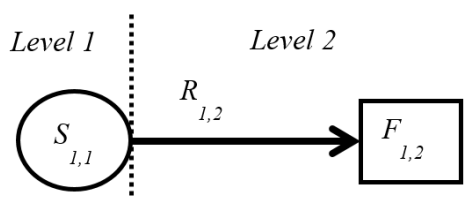

Figure 6.2. Basic supply chain system

Step 1. Calculate cumulative standard deviations (uncertainty) of the entity distribution functions. Since in this example all entities are assumed to be normally distributed, their sum is also normally distributed.

$$f_{S(1,1)\sum_{j=1}^{1}\sum_{i=1}^{1}\sigma_{1,1}} = \sqrt{3^2} = 3$$

$$f_{R(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}\sigma_{i,j}} = \sqrt{3^2 + 4^2} = 5$$

$$\underset{F(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}\sigma_{i,j}}{f} = \sqrt{3^2+4^2+3^2} = 5.8310$$

Step 2. Calculate the cumulative delay function due waiting time that entity *i* spent waiting for products from the previous factory in previous level *j-1*.

$$\underset{S(1,1)\sum_{j=1}^{1}\sum_{i=1}^{1}\varepsilon_{i,j}}{f} = 0$$

$$\underset{R(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}\varepsilon_{i,j}}{f} = 0+(30-25) = 5$$

$$\underset{F(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}\varepsilon_{i,j}}{f} = 0+(30-25)+0 = 5$$

Step 3. Calculate the reliability rate of each entity in the system. Since the sum of the delay ($\varepsilon_{i,j}$) and uncertainty ($\sigma_{i,j}$) is less than the due time (T^T), the reliability rate ($\Omega_{i,j}$) can be calculated as follows:

$$\Omega_{S(1,1)} = \left(80-(3+0)\right)\times\frac{1}{80} = 0.9625$$

$$\Omega_{R(1,2)} = \left(80-(5+5)\right)\times\frac{1}{80} = 0.8750$$

$$\Omega_{F(1,2)} = \left(80-(5.8310+5)\right)\times\frac{1}{80} = 0.8646$$

In conclusion, the reliability rate for this SCS is 86.46%, as shown in Figure 6.3. The total actual cycle time to complete the required job is 97.8310 hours, which can be calculated as

$$T_{i,j} = \sum_{i=1}^{I} \underset{(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\mu_{i,j}}{f} + \underset{(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{i,j}}{f} + \underset{(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{i,j}}{f} \tag{6.3}$$

$$\underset{S(1,1)}{T} = 30+3+0 = 33$$

$$\underset{R(1,2)}{T} = 30+25+5+5 = 65$$

$$T_{F(1,2)} = 30+25+32+5.8310+5=97.8310$$

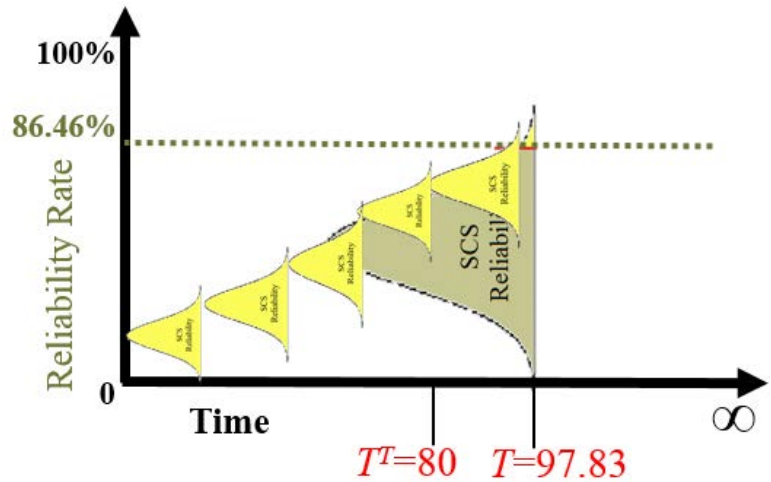

Figure 6.3. SCS reliability rate

Once the reliability rate is calculated, improvements on the overall supply chain system can be determined by implementing successive improvements to any entity in the SCS. Specific identified processes in factories and routes can be targeted in order to improve the overall reliability rate.

6.3. Design Optimization for Reliability in Supply Chain Systems

The main aim of the developed optimization algorithm is to design a reliable supply chain system with inherent robustness. The objective function of this optimization algorithm is to minimize delay and variability between system entities. While constraints are required, reliability rates of each entity and overall system. In this research, objective function components are considered to be equally important. However, in different cases, different weightings can be assigned to each of the objective function components. Many research studies have emphasized that multiple objectives can be combined into a single objective function by adding the weighted sum of all (Deb, 2001; Konak et al., 2006; Murata et al., 1996; Yildirim & Mouzon, 2012). The weight can be assigned based on the importance of the component on the objective function. More

details on determining the optimal weights in multiple objective function optimization can be found in the work of Gennert and Yuille (1988).

Minimize

$$\omega_1 * f_{X(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{X(i,j)}} + \omega_2 * f_{X(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{X(i,j)}}$$

Subject to

$$\begin{aligned}
&\Omega_{X(i,j)} \geq \Omega^T_{X(i,j)} \\
&f^l_{\mu_{X(i,j)}} \leq f_{\mu_{X(i,j)}} \leq f^u_{\mu_{X(i,j)}} \\
&T^T \leq \left(f_{X(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{X(i,j)}} + f_{X(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{X(i,j)}} \right) \quad , \quad i = 1,2,...,I \\
&f_{\mu_{X(i,j)}} \geq 0 \quad , \quad j = 1,2,...,J \\
&\sum_{n=1}^{N} \omega_n = 1 \quad , \quad n = 1,2,...,N
\end{aligned} \tag{6.4}$$

where $\sigma_{X(i,j)}$ represents the standard deviations (delay due to internal uncertainty) of the total cycle time function of entity type *X* number *i* in level number *j*, $\varepsilon_{X(i,j)}$ is the delay function of entity type *X* number *i* in level number *j* (delay due time that entity type *X*, number *i* in level number *j* spent waiting for products from the previous entity type *X* number *i* in level number *j-1*), ω_n is the weight attached as per the decision-maker preference, $\Omega_{X(ij)}$ is the reliability rate function of the *i*th entity type *X* on level j, $\Omega^T_{X(ij)}$ is the target reliability rate value for the *i*th entity Type *X* on level *j*, $\mu_{X(i,j)}$ is the design variable for the mean time to complete the required job at entity type *X* number *i* in level number *j*, $\mu^l_{X(i,j)}$ and $\mu^u_{i,j}$ are the lower and upper limits of the *X(i,j)* design variable, respectively, T^T represents the system total target cycle time, and *X* represents the type of entity, which can be route (R), factory (F), or supplier (S).

6.4. Design Case Study

This case study, considers the case of a company that operates a complex supply chain system consisting of connected parallel and series suppliers, factories, distribution center, and

retailer. This case study is performed to test the efficacy of the preformed methodology for evaluating and optimizing reliability rate of all entities in the system. This SCS consist of 4 stages for different type of operation which are suppliers' stage, factories' stage, distribution centers' stage, and retailers' stage. And has 5 phases that contains 26 entities. It consist of four suppliers, six factories, one distribution center, one retailer, and 14 routs. The required reliability rate in this case study is 90%.

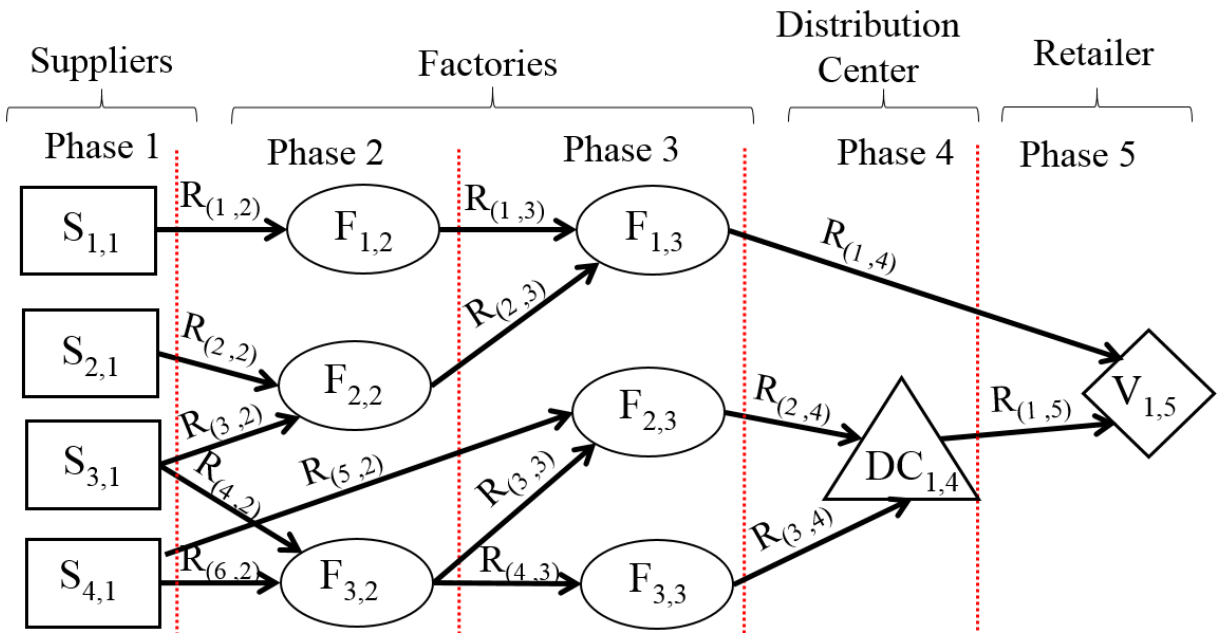

Figure 6.4. Case study - complex SCS

The SCS for the company can be divided into four major stages and five phases:

- **Stage 1 (phase 1)**: Suppliers of raw materials used in different products.
- **Stage 2:** Consist of two phases. **Phase 2** Factories produce material to be used in producing multiple products, and **phase 3** factories produce final products.
- **Stage 3 (phase 4)**: Distribution centers.
- **Stage 4 (phase 5)**: Retailer.

Figure 6.4 represents the case study complex supply chain system, where S_{ij} denotes supplier number *i* at level number *j*, F_{ij} denotes factory number *i* at level number *j*, DC_{ij} denotes distribution center number *i* at level number *j*, V_{ij} denotes retailer number *i* at level number *j*, and R_{ij} denotes route number *i* at level number *j*. In this SCS it is assumed that factories cannot start the required job until receiving all required parts. For example, factory $F_{1,3}$ will not start until it receives the required parts from factory $F_{1,2}$ and factory $F_{2,2}$. For the purpose of this case study, the collected data (design parameters) were assumed to be normally distributed and their means and standard deviations are shown in Tables 6.1 – 6.4. Where Table 6.1 displays supplier design parameters, Table 6.2 displays factories design parameters, Table 6.3 shows distribution center and retailer design parameters, and Table 6.4 shows routs design parameters. To solve this case study, the SCS was modeled in MATLAB R2013a.

TABLE 6.1

SUPPLIER DESIGN PARAMETERS

SCS Supplier	**Mean Time (μ) (hr/batch)**	**Time Variation (σ) (hr/batch)**
Supplier 1 ($S_{1,1}$)	180	22
Supplier 2 ($S_{2,1}$)	300	80
Supplier 3 ($S_{3,1}$)	480	41
Supplier 4($S_{4,1}$)	180	60

TABLE 6.2

FACTORIES DESIGN PARAMETERS

SCS Factories	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Factory 1 ($F_{1,2}$)	120	15
Factory 2 ($F_{2,2}$)	220	30
Factory 3 ($F_{3,2}$)	180	33
Factory 4 ($F_{1,3}$)	280	44
Factory 5 ($F_{2,3}$)	350	56
Factory 6 ($F_{3,3}$)	250	29

TABLE 6.3

DISTRIBUTION CENTER AND RETAILER DESIGN PARAMETERS

SCS Distribution Center and Retailer	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Distribution Center 1 ($DC_{1,4}$)	180	44
Retailer 1 ($V_{1,5}$)	290	33

TABLE 6.4

ROUTES DESIGN PARAMETERS

SCN Routes	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Route 1 ($R_{(1, 2)}$)	195	20
Route 2 ($R_{(2, 2)}$)	80	44
Route 3 ($R_{(3, 2)}$)	140	33
Route 4 ($R_{(4, 2)}$)	220	22
Route 5 ($R_{(5, 2)}$)	303	19
Route 6 ($R_{(6, 2)}$)	240	15
Route 7 ($R_{(1, 3)}$)	233	23
Route 8 ($R_{(2, 3)}$)	450	26
Route 9 ($R_{(3, 3)}$)	149	17
Route 10 ($R_{(4, 3)}$)	122	14
Route 11 ($R_{(1, 4)}$)	230	11
Route 12 ($R_{(2, 4)}$)	320	27
Route 13 ($R_{(3, 4)}$)	211	30
Route 14 ($R_{(1, 5)}$)	178	50

First, the SCS mathematical model was implemented in MATLAB to measure the initial system performance using equation (6.2). Then the developed optimization model equation (6.4) is applied. Results of this case study are shown in Tables 6.5 – 6.10. Table 6.5 shows suppliers' objective optimal mean time, calculated initial reliability rate, and optimal reliability rate. Table 6.6 illustrates factories' objective optimal mean time, calculated initial reliability rate, and optimal reliability rate. Table 6.7 illustrates distribution center and retailer objective optimal mean time, calculated initial reliability rate, and optimal reliability rate. Table 6.8 illustrates routs' objective optimal mean time, calculated initial reliability rate, and optimal reliability rate. Table 6.9 illustrates objective optimal reliability rate of SCS phases, initial design reliability rate, initial

design delay, and optimal design delay. Table 6.10 presents objective values obtained at each iteration.

TABLE 6.5

OBJECTIVE OPTIMAL SUPPLIER RELIABILITY RATE

SCS Supplier	Optimal Mean Time (μ) (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Supplier 1 ($S_{1,1}$)	245.7292	99.05	98.96
Supplier 2 ($S_{2,1}$)	181.1038	96.68	98.07
Supplier 3 ($S_{3,1}$)	214.6045	98.22	99.05
Supplier 4($S_{4,1}$)	209.265	97.32	98.69

TABLE 6.6

RELIABILITY RATE OF FACTORIES FOR OPTIMAL OBJECTIVES

SCS Factories	Optimal Mean Time (μ) (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Factory 1 ($F_{1,2}$)	247.5583	95.36	96.89
Factory 2 ($F_{2,2}$)	263.2087	82.83	98.66
Factory 3 ($F_{3,2}$)	197.3271	84.71	96.14
Factory 4 ($F_{1,3}$)	311.0315	74.74	95.59
Factory 5 ($F_{2,3}$)	281.0424	80.92	94.72
Factory 6 ($F_{3,3}$)	227.7399	82.84	92.20

TABLE 6.7

DISTRIBUTION CENTER AND RETAILER RELIABILITY RATE FOR OPTIMAL OBJECTIVE

SCS Distribution Center and Retailer	Optimal Mean Time (μ) (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Distribution Center 1 ($DC_{1,4}$)	212.456	73.01	90.84
Retailer 1 ($V_{1,5}$)	265.097	72.17	90.44

TABLE 6.8

RELIABILITY RATE OF ROUTES FOR OPTIMAL OBJECTIVE

SCN Routes	Optimal Mean Time (μ) (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Route 1 ($R_{(1, 2)}$)	319.3426	98.70	98.86
Route 2 ($R_{(2, 2)}$)	202.4697	87.14	98.02
Route 3 ($R_{(3, 2)}$)	251.581	83.20	99.01
Route 4 ($R_{(4, 2)}$)	245.8746	86.85	99.02
Route 5 ($R_{(5, 2)}$)	232.8306	97.22	98.66
Route 6 ($R_{(6, 2)}$)	257.5559	97.22	98.65
Route 7 ($R_{(1, 3)}$)	208.9099	95.06	96.83
Route 8 ($R_{(2, 3)}$)	268.7244	82.79	98.66
Route 9 ($R_{(3, 3)}$)	299.6555	83.20	96.14
Route 10 ($R_{(4, 3)}$)	296.1654	81.95	96.10
Route 11 ($R_{(1, 4)}$)	262.0642	72.57	93.81
Route 12 ($R_{(2, 4)}$)	267.5808	79.44	94.11
Route 13 ($R_{(3, 4)}$)	192.9557	80.29	90.35
Route 14 ($R_{(1, 5)}$)	218.1367	72.38	90.77

TABLE 6.9

RELIABILITY RATE OF SCS PHASES FOR OPTIMAL OBJECTIVE

SCS Phases	Initial Delay (hr/batch)	Design Delay (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Phase 1	76.9171	42.423	96.68	98.07
Phase 2	107.4372	29.4048	82.83	96.89
Phase 3	585.8251	171.7222	74.74	92.20
Phase 4	626.0413	201.6248	73.01	90.84
Phase 5	645.5253	210.4331	72.17	90.44

TABLE 6.10

OBJECTIVE VALUES OBTAINED AT EACH ITERATION

Iteration	Objective (hr/batch)	Iteration	Objective (hr/batch)	Iteration	Objective (hr/batch)
0	0	**7**	274.346	**14**	279.136
1	305.871	**8**	270.871	**15**	226.178
2	289.857	**9**	273.07	**16**	223.169
3	298.012	**10**	276.933	**17**	217.106
4	382.771	**11**	271.199	**18**	211.314
5	275.645	**12**	364.081	**19**	210.8725
6	275.62	**13**	274.465	**20**	210.4331

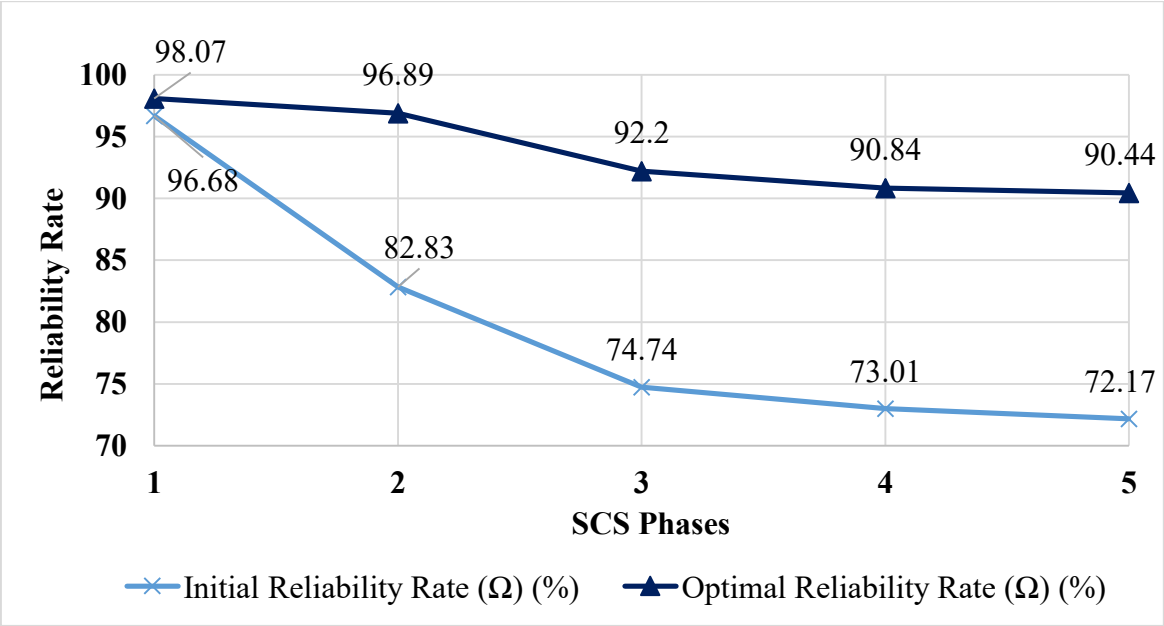

Figure 6.5. Reliability rate of all phases

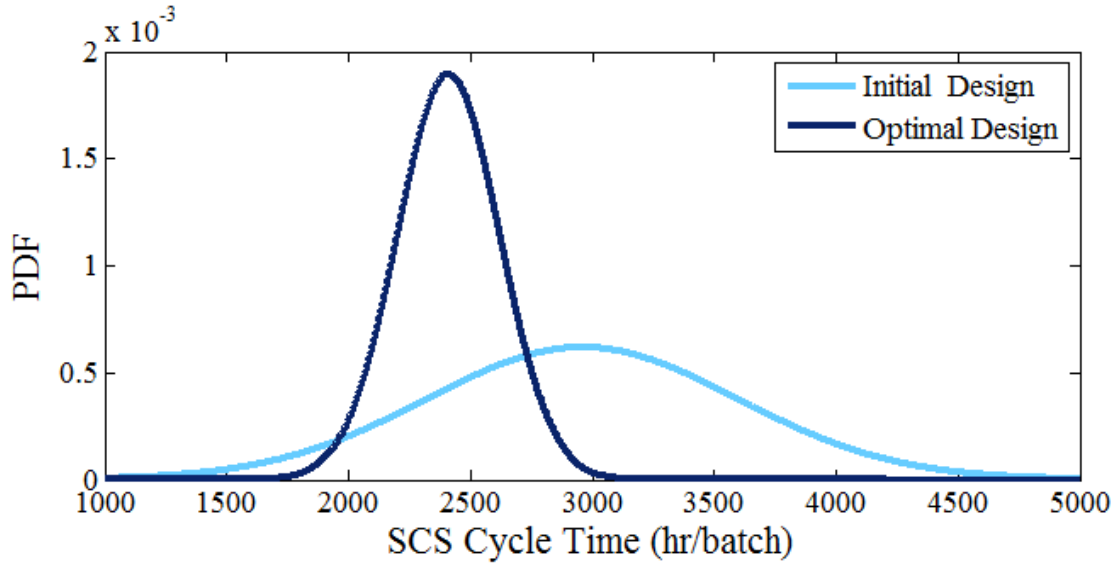

Figure 6.6. Distributions of SCS mean cycle time

By applying developed optimization model, the required reliability rate was achieved and delay was minimized. From Table 6.9, it is clear that SCS delay and uncertainties were decreased from 645.5253 hours per batch in the first initial design to 210.4331 hours per batch in the final iteration in the optimal design. Also, all constraints were satisfied, as shown in Tables 6.5 – 6.10, the highest reliability rate for the optimal design is at level one with 99.05%. In contrast, the lowest reliability rate is 90.04% which represents the overall SCS reliability rate.

In Figure 6.5, it can be easily seen that the reliability rate of the SCS decreases from the first phase to the fifth phase in the system. For example, the reliability rate in the initial SCS design for phase 1 is 96.68%, whereas in phase 2 the reliability rate is decreased by 13.85% to 82.83%. This decrease is caused by uncertainties and different processing and transportation times between entities. The overall reliability rate of the initial SCS design is low (72.17%). In order to reduce total cycle time and satisfy a 90% reliability rate, the developed optimization model is applied.

Figure 6.6 compares the initial and final probability density functions of the system. By comparing distributions of the mean cycle time of optimal design and initial SCS design, the time

variation is significantly reduced because the total delay in the system was reduced by 435.0922 hours. The developed optimization model resulted in a lower mean cycle time where the mean cycle time of the SCS is reduced by 553.3183 hours from 2,965.5253 hours to 2,412.2076hours. When comparing initial system design and optimal design, it is clear that developed system design has less cycle time and delay, and satisfies the required reliability rate. This optimization helps to determine the entities that should be improved and the level of improvement that should be attained to satisfy the system's reliability rate.

6.5. Conclusion

As more and more companies are involved in outsourcing and building factory supply chains, there is an urgent need to develop the concept of a supply chain system reliability rate for a factory-to-factory SCS. This paper has focused on maintaining reliability rates at each step in the SCS. Also, this research adds more value by developing an optimization approach for SCS when one factory supplies to another factory. This study examined the effects of uncertainty and delays introduced by production and transportation on overall reliability rate requirements. In summary, what has been presented here is a novel design optimization methodology to derive designs of factories and the reliability rates of routes in order to satisfy the reliability rate requirement. As future work, the cost of improving the reliability rate of each entity will be added to the optimization techniques so that the required reliability rate can be satisfied with the lowest cost possible.

CHAPTER 7

MEASUREMENT OF RESILIENCE IN MULTI-LEVEL SUPPLY CHAIN SYSTEMS

7.1 Introduction

In the emerging area of supply chain system management under uncertainty, resilience has been rarely studied. In the case of an upstream factory-to-factory supply chain system, the resilience concept remains unexplored. The word "resilience" is adopted from the Latin 'resiliō', which means recoiling, springing back, rebounding. In English, resiliō means reacting to a return to actual size. For the last four decades, resilience has been used in many different fields, including organizational management, social engineering, economy, ecology, and psychology. Also, the meaning of resilience is based on research perspectives. For example, in ecology, resilience can be defined as the ability of an ecosystem to resist and recover quickly from disturbance (Ponis & Koronis, 2012). Supply chain system resilience can be defined as the ability of an SCS to return quickly to normal performance after a disruption. To measure this resilience, it must be properly defined within the context of an SCS, and then the relationship between the various supply chain elements must be studied. It is also necessary to identify the link between risks and uncertainties in the SCS and develop approaches for managing resilience issues. The aim of this chapter is to define and explore supply chain system resilience models and theories, and develop an innovative quantitative measure to calculate SCS resilience.

This chapter intends to provide a study on supply chain risk and resilience. It also addresses challenges due to complexity in products, diversity of suppliers, end-customers' geographic distribution, and the intertwined industry relationships and processes among suppliers, manufacturers, distributors, retailers, and customer requirements. The need exists for a research and methodology that can provide an assessment of the efficiency of a supply chain system

configuration. The resilience of SCS designs when interactions occur among connected factories and these interactions impact the overall SCS resilience has been rarely studied and remains almost untouched. The remainder of this paper is organized as follows. Section 7.2 introduces a novel SCS resilience measure and how a developed resilience measure can be calculated using a numerical example. Section 7.3 illustrates the ability of the developed model to quantify the resilience of a complex SCS through a case study. Finally, in section 7.4, the chapter ends with a brief conclusion.

7.2 Model for Measuring Supply Chain System Resilience

This section explains the developed supply chain system resilience measure. In order to design a resilient SCS, the term "resilience measure" should be defined. Also, a constant range limit of this measure must be identified to compare the actual system performance with the target performance. Once system evaluations are completed, specific identified processes in the SCS can be targeted in order to improve the overall SCS resilience. Thus, in this research, a resilience measure of an SCS is developed. Supply chain system resilience can be defined as the rate at which the system recovers to original performance levels after a disruption. It also defines the system's ability to absorb high-risk impacts, including workforce strikes, security discrepancies, and physical disasters such as earthquakes, hurricanes, fires, and storms. This research focuses on evaluating SCS resilience based on observing high-risk impacts. Therefore, in general, system resilience is defined by how fast the system recovers after a disruption. However, the ability of a system to recover also depends on the magnitude and time of disruption. Thus, in defining resilience, the measure is tied to the magnitude of the disruption. For purposes of this paper, disruption time is defined as the time between the instant at which the disruption started until the system is fully recovered. Also, recovery for the supply chain is tracked as soon as the disruption

occurs. To develop the supply chain system resilience measure, consider the case of a company that manufactures different types of products and purchases its supply from one supplier that could be a manufacturing plant. Supplier S_i can supply up to x number of the demand p for factory F_i to produce product z (Figure 7.1). Supplier S_i spends time t_i to produce x number of the demand p for factory F_i. And factory F_i spends time t_i to complete producing the required product z. Thus, the company spends a total time of T_i to produce product z. Also, the company must manufacture product z by the due date T^T. This interaction between supplier and factory can be expressed mathematically as $x = p$, where the output x of supplier S_i must be equal to the quantity p that factory F_i ordered to produce product z.

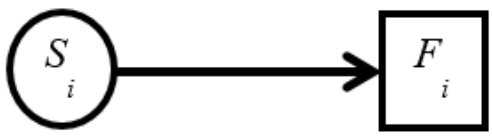

Figure 7.1. Typical upstream supply chain system

If there is a high-risk disruption, such as a fire or tornado, which impacts supplier S_i, or if the demand fluctuates and results in an increased demand by "x" units beyond the capacity of supplier S_i, then factory F_i will not be able to produce the products or satisfy the required demand. In such a situation, it can be stated that the supply chain system is not resilient for a high-risk disruption. If the SCS is resilient, then it must operate normally (at 100%) before, during, and after a disruption. To illustrate, if the system reliability rate is 90%, then the system reliability rate must be at 90% during normal operation and disruption, as shown in Figure 7.2. The procedure for calculating the reliability of an SCS can be found in Chapter 6.

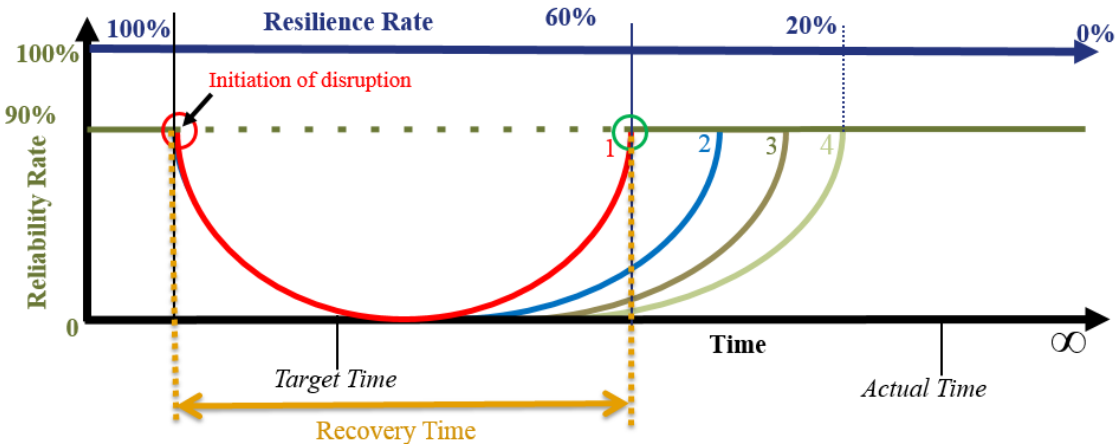

Figure 7.2. Resilience phenomenon

Figure 7.2 shows that the current system reliability rate is 90%. If the system is 100% resilient and a disruption occurs, then it should continue to operate normally and have a 90% reliability rate. However, if the system were not able to perform the required function during the disruption, then it is not resilient. For instance, if the system reacts and bounces back according to line #1 (shown in Figure 7.2), then this indicates that the system has a resilience of 60%. Similarly, if the system follows lines #2, #3, and # 4, respectively, then the system is at a resilience of 50%, 35%, and 20%, respectively. Also, if the system cannot return to normal activity, then the system has 0% resilience. Resilience in the context of supply chain systems is defined by the rate of recovery after a disruption:

$$\varphi = \frac{T^T + \varepsilon}{T^T + \varepsilon + \theta} \tag{7.1}$$

where φ represents the resilience rate, T^T is the target time, ε is the internal delay due to internal uncertainty (low risks such as production delays, transportation delays, defective components, etc.), and θ is the external delay due to external uncertainty (high risk such as fire, workforce strike, security discrepancy disruption, etc.). Equation (7.2) can be used to calculate SCS resilience:

$$\varphi_{X(i,j)} = \frac{T^T + f_{X(i,j)} \sum_{j=1}^{J}\sum_{i=1}^{I} \sigma_{X(i,j)} + f_{X(i,j)} \sum_{j=1}^{J}\sum_{i=1}^{I} \varepsilon_{X(i,j)}}{T^T + f_{X(i,j)} \sum_{j=1}^{J}\sum_{i=1}^{I} D_{X(i,j)} + f_{(i,j)} \sum_{j=1}^{J}\sum_{i=1}^{I} \sigma_{X(i,j)} + f_{(i,j)} \sum_{j=1}^{J}\sum_{i=1}^{I} \varepsilon_{X(i,j)}}$$

$$\text{where} \tag{7.2}$$

$$\varepsilon_{X(i,j)} = \begin{cases} if \;\; f_{\mu X(i,j-1)} > f_{\mu X(i,j)} \;, \quad f_{\mu X(i,j-1)} - f_{\mu X(i,j)} \\ 0 \;\; otherwise \end{cases}$$

where $\varphi_{X(i,j)}$ is the resilience rate of entity type X number i in level number j to complete the required job, T^T represents the due time, $\sigma_{X(i,j)}$ is the standard deviation (uncertainty) of entity type X number i in level number j to complete required job, $\varepsilon_{X(i,j)}$ is the delay function due to the time that entity type X number i in level number j spent waiting for products from the previous entity type X number i in previous level j-1, $\mu_{X(i,j)}$ is the mean time of entities to complete a required job at entity type X number i in level number j, $D_{X(i,j)}$ represents the recovery time for entity type X number i in level number j, X represents the type of entity, which can be route (R), factory (F), or supplier (S), i represents the entity number, and j represents the level number.

7.2.1 Numerical Example

This example consists of a supply chain system that has two levels and three entities Figure (7.3). These entities are supplier ($S_{1,1} = N(30,3^2)$), route ($R_{2,1} = N(25,4^2)$), and factory ($F_{2,1} = N(32,3^2)$). The due date to complete one batch is 80 hours ($T^T = 80$). The objective of this example is to measure the resilience rate using the developed measure. Two scenarios are applied: no disruption, and a disruption that takes 168 hours (two weeks, assuming the system works 12 hours a day) to recover.

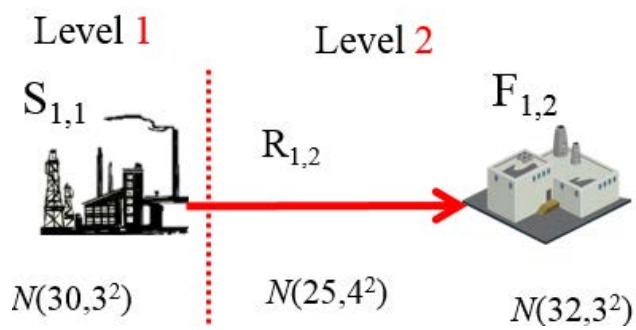

Figure 7.3. Supply chain system

Step 1. Calculate the cumulative standard deviations (uncertainty) of the disruption time of each entity's distribution function. Since in this example all entities are assumed to be normally distributed, their sum is also normally distributed.

$$f_{S(1,1)\sum_{j=1}^{1}\sum_{i=1}^{1}\sigma_{1,1}} = \sqrt{3^2} = 3$$

$$f_{R(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}\sigma_{i,j}} = \sqrt{3^2 + 4^2} = 5$$

$$f_{F(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}\sigma_{i,j}} = \sqrt{3^2 + 4^2 + 3^2} = 5.8310$$

Step 2. Calculate the cumulative delay function associated with the time that entity *i* spent waiting for products from a previous factory in a previous level *j-1*.

$$f_{S(1,1)\sum_{j=1}^{1}\sum_{i=1}^{1}\varepsilon_{i,j}} = 0$$

$$f_{R(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}\varepsilon_{i,j}} = 0 + (30 - 25) = 5$$

$$f_{F(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}\varepsilon_{i,j}} = 0 + (30 - 25) + 0 = 5$$

Step 3. Calculate the cumulative recovery time function of each entity when disruption occurs.

$$f_{\mathrm{S}(1,1)\sum_{j=1}^{1}\sum_{i=1}^{1}D_{i,j}} = 168\,\mathrm{hr}.$$

$$f_{R(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}D_{i,j}} = 168 + 0 = 168\,\mathrm{hr}.$$

$$f_{F(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}D_{i,j}} = 168 + 0 + 0 = 168\,\mathrm{hr}.$$

Step 4. Calculate the overall system resilience rate from equation (7.2).

When there is no disruption:

$$f_{F(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}D_{i,j}} = 0 + 0 + 0 = 0\,\mathrm{hr}.$$

$$\varphi = \frac{80 + 5.8310 + 5}{80 + 0 + 5.8310 + 5} = 1$$

When there is disruption for two weeks:

$$f_{F(1,2)\sum_{j=1}^{2}\sum_{i=1}^{1}D_{i,j}} = 168 + 0 + 0 = 168\,\mathrm{hr}.$$

$$\varphi = \frac{80 + 5.8310 + 5}{80 + 168 + 5.8310 + 5} = 0.3509$$

Figure 7.4 summarizes the result of reliability rate and resilience rate. When there is no disruption, system resilience is 100% with a reliability rate of 86.46%. However, when there is a disruption and the system takes two weeks to recover, the resilience rate is 35.09% with a reliability rate of 86.46%. To improve supply chain resilience, different strategies and techniques can be applied. For example, increasing flexibility in the system will increase the resilience of the system. This can be achieved by redundancy and extra production capacity. It can also be achieved by adding redundancies in suppliers or by identifying alternate suppliers that are not used currently

but can supply. Resilience can also be improved by increased information sharing and by adding buffers/storage space.

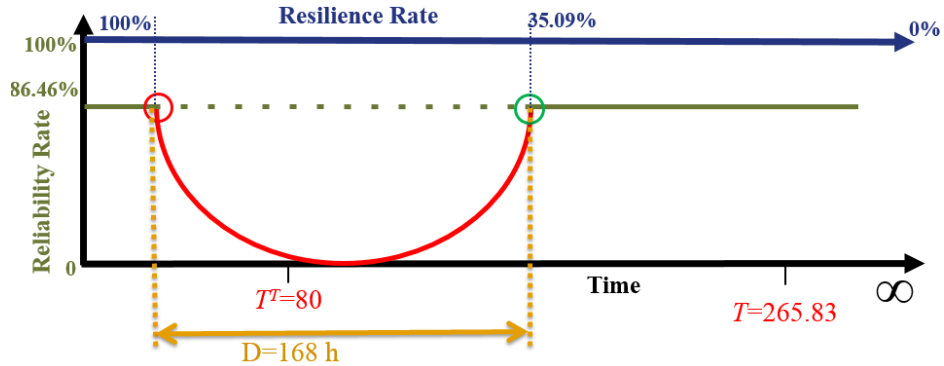

Figure 7.4. SCS resilience rate

7.3. Design Case Study

This case study is a complex supply chain system that consists of connected parallel and in series factories. It is performed to test the ability of the proposed resilience measure for measuring complex SCS resilience. The reliability rate in this case study is 90%. Figure 7.5 represents the complex SCS, where it is assumed that factories cannot start the required job until receiving all required parts from previous-level factories. For purposes of this case study, the collected data (design parameters) were assumed to be normally distributed, and their means and standard deviations are shown within parentheses. To solve this case study, first we redrew the supply chain system to make it easier for analysis (Figure 7.6). Figure 7.6 shows that this SCS consist of five levels and 17 entities comprised of eight factories (F) and nine routes (R).

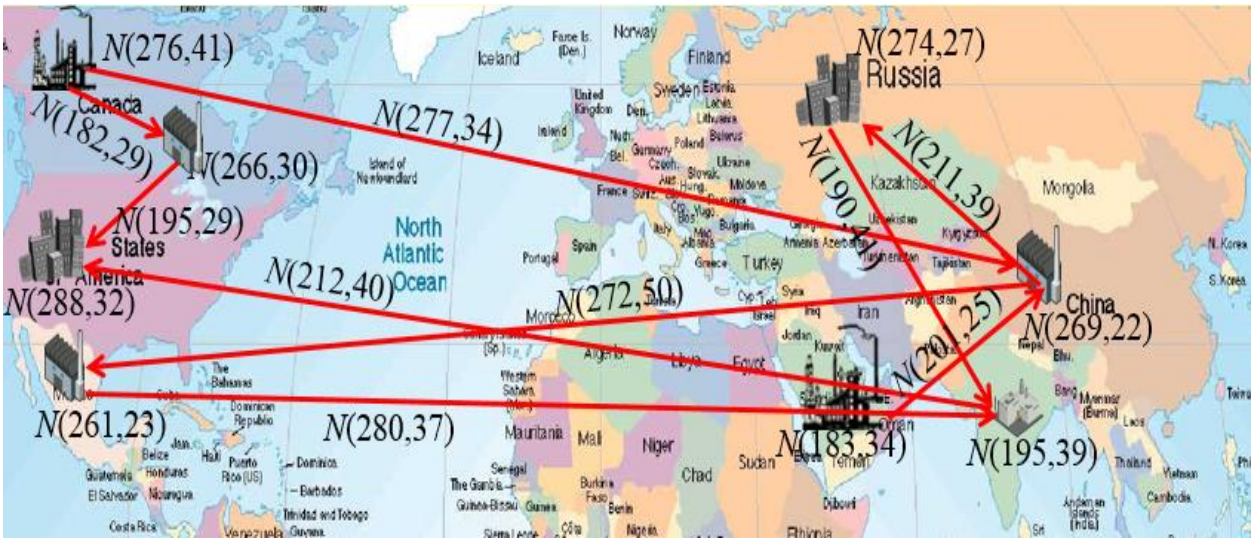

Figure 7.5. Physical complex SCS

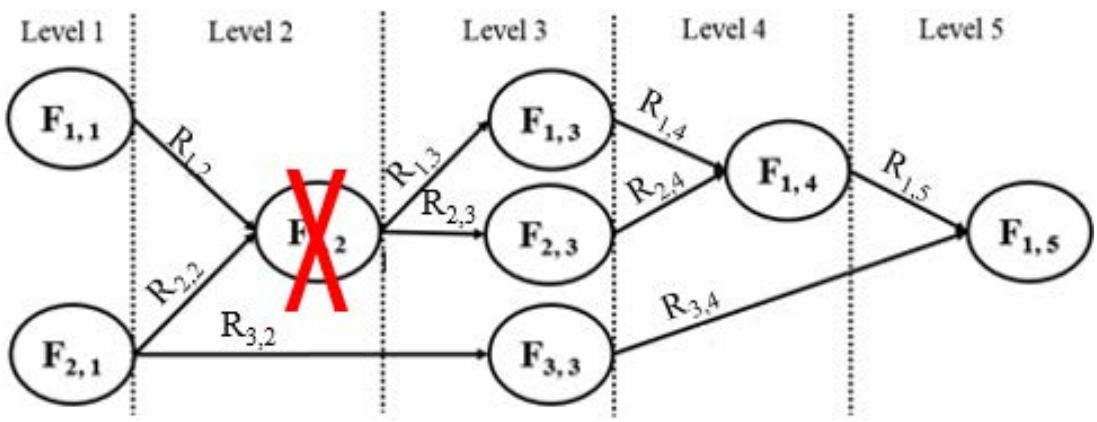

Figure 7.6. Case study complex SCS

Two scenarios have been applied to this case study:

- **Scenario one:** No disruption occurred.
- **Scenario two:** A disruption taking 45 days to recover (45 days *24 hours = 1,080 hours of disruption). The disruption is applied to $F_{1,2}$.

To solve this case study, the supply chain is modeled using mathematical simulation in MATLAB R2013a. Also, the measurement model has been applied to measure the system resilience rate. Outputs of this model are shown in Figures 7.7 and 7.8. Figure 7.7 displays the

reliability and resilience rates when there is no disruption, indicating that the overall system reliability rate is 90.87% and resilience rate is 100%. Figure 7.8 displays the reliability and resilience rates when there is a 45-day disruption, indicating that the overall system reliability rate is 90.87% and resilience rate is 70.19%.

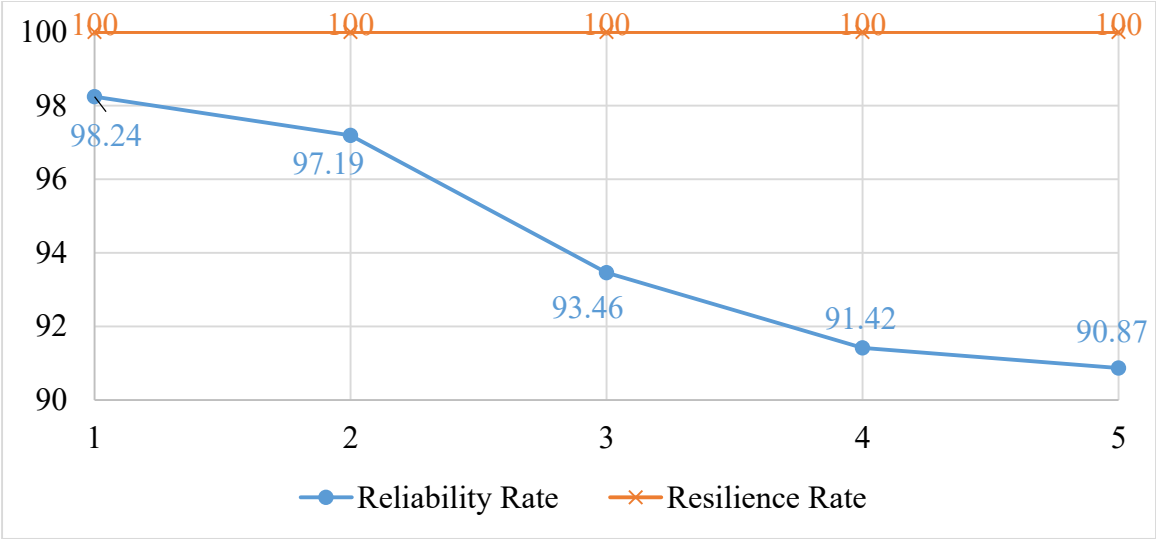

Figure 7.7. Reliability and resilience rates for scenario one

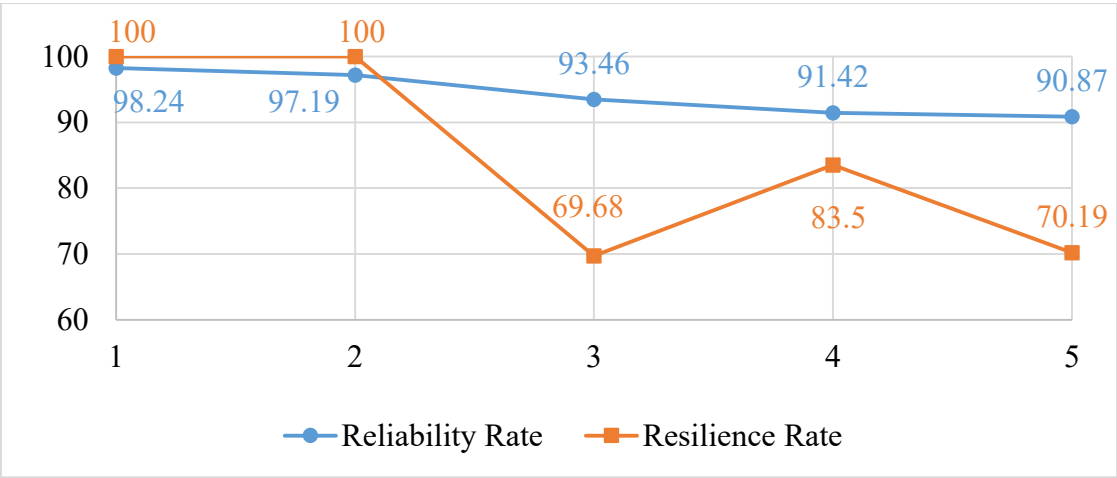

Figure 7.8. Reliability and resilience rates for scenario two

7.4. Conclusion

This chapter addressed the need of introducing a novel quantitative measure for determining resilience of supply chain systems. In the design of SCSs, this measure will improve the effectiveness of the design. The concept of resilience of a supply chain and its measure allows designers to effectively design SCSs that can withstand disruptions and provide service at pre-disruption levels. A numerical example was used to clarify and demonstrate the procedure for calculating resilience for each entity and for the overall system. The development of quantitative measures for resilience will allow supply chain designers to design resilient SCSs that are responsive to disturbances in the chain.

CHAPTER 8

MEASUREMENT AND ANALYSIS OF RELIABILITY, RESILIENCY, AND ROBUSTNESS IN COMPLEX SUPPLY CHAIN SYSTEMS

8.1 Introduction

Reliability and resilience of a supply chain system are important for companies to remain competitive. Moreover, it is also important for companies to design supply chains that are robust which will help to ensure reliability and resilience of the system. In the case of a supply chain impacted by disruptions, the SC must be designed to allow corrective action that restores its reliability rate to predisruption levels. This chapter introduces the concept of SC robustness. In this chapter, a method is developed for measuring the robustness of supply chain systems and all system entities.

The main thrust of this research was to develop innovative supply chain system performance measures that can effectively evaluate SCSs considering uncertainties when the system is in normal or disruptive conditions. The new performance measures that have been developed in previous chapters are reliability rate and resilience rate. In this chapter, a new measure is being introduced to measure SCS robustness—a methodology to evaluate and analyze factory-to-factory SCSs robustness.

In Chapters 6 and 7, methods for evaluating supply chain system reliability and resilience were developed and discussed. This chapter will introduce another method to evaluate supply chain system resilience. The remainder of this chapter is organized as follows. Section 8.2 illustrates how developed measurement models should be applied to a supply chain system. Section 8.3 contains methodologies to reduce the impact of uncertainty and increase SCS reliability, resiliency, and robustness. Section 8.4 introduces a novel robustness measure in order

to evaluate SCS robustness and assist management in decision making. In section 8.5, a complex SCS case study illustrates and assesses the effectiveness of the proposed approach. Finally, the chapter ends with section 8.6 and a brief conclusion.

8.2 Reliability, Resiliency, and Robustness Implementation Procedure

In order to design a resilient and robust supply chain system evaluation measures should be defined. Also, a constant range limit of these measures must be identified to compare actual system performance and target performance. Once system evaluation is completed, specific identified processes in the SCS can be targeted in order to improve its overall reliability, resilience, and robustness. Thus, reliability, resilience, and robustness measures have been developed. In order to effectively apply these measures, the procedure shown in Figure 8.1 should be followed,

Figure 8.1. Performance measurement and analysis development procedure

The first step in this procedure is to understand the system characteristics. Second, all supply chain system members should be involved and should clearly understand the network performance measurements. Third, a clear objective is defined, where all activities and performance aspects in the supply chain system are dedicated to common objectives such as minimizing the cost of failure, increasing reliability, and being robust. The fourth step involves applying a performance measurement and development analysis throughout the supply chain

system. The fifth step is to monitor each entity in the system, which can be completed by identifying an ideal range limit for the process parameters performance so that target and actual reliability, resilience, and robustness rates can be associated for comparison analysis. The sixth step is identifying a specific processes in an entity in the system to be targeted for improvement. Finally, the seventh step is achieving required robustness rate and control it.

This chapter helps to evaluate SCSs and assists high-level management in decision making. These measures are reliability rate, resilience rate, and robustness rate:

- *Reliability Rate* (Ω): The ability of the system to absorb low-risk impacts and complete required tasks on time. This also measures customer satisfaction based on receiving required products on time during period of low risk.
- *Resilience Rate* (φ): The rate at which the system recovers to the original performance levels after a disruption. This also defines the ability of the system to absorb high-risk impacts.
- *Robustness Rate* (ψ): The ability of the system to work during low and high risks, the ability to absorb changing circumstances, and the sensitivity of the system to unknown variations.

8.3 Approaches to Improve Supply Chain System Reliability, Resiliency, and Robustness

Meeting the due dates for orders is an important and highly complex work in factory-to-factory supply chain systems. In order to achieve on-time deliveries of orders, production and transportation lead times in the system should be controlled. In general, lead time is defined as the time between the release of an order and the order due date. The most important aspect that plays a major rule in a SCSs' reliability, resiliency, and robustness is time. Time should be constant for all activities in the system, but because of variability, there are delays. Reliability and resilience of an SCS depends on characteristics of the system variability and the resulting delays. The resilience

definition and calculation are based on the disruption time period and the time taken by the system to recover after disruption. The SCS is considered to be robust when there is less delay in the system. Hsu and Li (2011) showed that many industries have acknowledged the importance of lead time and its impact on industries. Hammami and Frein (2013) emphasized that due dates for delivery that can be promised by companies must be less than the customer due date. Also, their research confirms that there is a lack of SC design models that consider customer lead time constraints in a global multi-echelon SC. They added a lead-time constraint to their optimization model to design a global multi-echelon SC. Also, Eskigun et al. (2005), Meixell and Gargeya (2005), Vidal and Goetschalckx (1997), and You and Grossmann (2008) have illustrated that lead time should be considered during the design of the SCS. To enhance the performance of an SCS, all activity in the system that is related to time should be controlled. Reliability, resiliency, and robustness of an SCS can be enhanced by minimizing and maintaining cycle time uncertainty and disruption. Also, it is important to be aware of delay factors. For example, delay can be caused by external factors such as traffic, customs delays, weather, etc. Delay can also be caused by internal factors such as scheduling errors, misplacement of parts, machine breakdowns, etc.

Numerous studies have been aimed at designing an SCS while considering uncertainty. Azaron et al. (2008) developed a multi-objective stochastic programming approach for SC design under uncertainty. Santoso et al. (2005) proposed a programming model and solution algorithm for solving SC network design problems while considering uncertainty. Their objective function minimized the total investment and operational costs, focusing on developing an accelerated optimization approach through an integrating sampling strategy, in which the sample average approximation was identified using an accelerated Benders decomposition algorithm. Yu and Li (2000) formulated a stochastic problem as a robust optimization model so that solutions become

less sensitive to data in the scenario set. Solutions were obtained by transforming a robust model into a linear program. Shi et al. (2014) developed a structural decomposition approach for the dynamic fleet management problem with uncertain demand. Benyoucef et al. (2013) developed a Lagrangian relaxation-based approach for SC network design with unreliable suppliers. In general, approaches that help to minimize cycle time and mitigate the impact of disruptions are summarized below:

- *Redundancy in Suppliers*: Redundant suppliers would reduce the impact of shortage and risk associated with delays for a part. In this way, whenever there is a disruption from one of the suppliers, other suppliers can produce additional products to overcome the impact of the disruption. Parlar (1997) and Parlar and Defne (1991) considered external suppliers as a solution for disruption in their developed model. In their studies, they assumed that all suppliers have infinite production capacity and identical cost. Yang (2009) developed a study in which an external supplier is used only when the parallel supplier is disrupted or is not able to deliver all required parts or products. Tomlin (2006) studied a single-product setting in which a firm can source from two suppliers—one that is unreliable and another that is reliable but more expensive. That study concluded that it is more cost effective to have an expensive supplier rather than holding extra inventory when the length of a disruption is long.
- *Shorter Supply Chains*: Shorter supply chains lead to smaller shipping times. It is better to have a local supplier because shipping time will be shorter. Also, uncertainty and delay will decrease since short distances can usually be managed easier. The time variability for short supply chains is usually less than that for long supply chains in terms of absolute values. For example, if the SC sources a manufacturer from China for a product to be

delivered in the US, the product must undergo shipping, possible delay at inspection during customs clearance, delay at the dock, and then delay in shipping within the US. However, if the same product is manufactured locally, the impact of all other delays are nullified.

- *Buffers and Depots*: Maintaining a buffer inventory is a legitimate policy for mitigating the impact of plant disruptions. In a traditional supply chain system, depots/distribution centers are used in routes to minimize the impact of uncertainties in delivery times. Holding extra inventory over safety stock and cycle stock to enhance supply chain performance has been discussed and identified in numerous research (Arreola-Risa & DeCroix, 1998; Parlar & Defne, 1991; Qi et al., 2010). Tomlin and Wang (2012) point out that holding extra inventory can protect supply chain systems against disruption. However, when the disruption time is high, a large amount of extra inventory is required and the cost can be significant. Thus, alternate procedures to minimize the impact of the delay should be developed. In addition, the number and the size of buffers and depots must be minimized in order to save costs. In the case of supply chains that are more upstream, a distributed buffer system rather than a central warehouse will be needed.
- *Supply Chain Flexibility*: A flexible supply chain will reduce the risk of disruption. One method of increasing flexibility is to provide alternate shipping routes that can help overcome disruption impact. Gosling et al. (2010) proposed supply chain flexibility as a determinant of supplier selection. Wang (2013) increased supply chain robustness through process flexibility and strategic inventory. Calantone and Dröge (1999) defined flexibility as "shared responsibility of two or more functions along the supply chain." Garavelli (2003) considered flexibility as "the ability of a supply chain to properly and rapidly respond to changes, coming from inside as well as outside the system." Das and Abdel-

Malek (2003) have stated that "supply chain flexibility is the elasticity of the buyer-supplier relationship under changing supply conditions."

- *Product Design Simplification*: Reducing the number and variety of parts in a product can also help in mitigating supply chain disruptions. When the number of parts is high, the system will be more sensitive to disruption and the probability of delay of required parts increases. Similarly, as the variety of products that are required in building a part increases, the chances of disruption and delays increase. One way to minimize the number of parts is to design standardized parts that can be used to build more than one product.
- *Effective Communication and Data Sharing*: The importance of an effective information system cannot be overemphasized in the ability of a supply chain to reduce the impact of disruptions. Organizations should invest in data sharing information systems to monitor supply chain systems. Data sharing will allow the use of strategic alternate plans to decrease the risk of disruption, and also help to increase the accuracy of disruption forecasting and allow for planning ahead for disruptions.

8.4 Model for Measuring Supply Chain System Robustness

In this section, a supply chain system robustness measure is developed. This measure evaluates the ability of an SCS to perform the required job based on system ability to complete the required job on time under any type of uncertainty and risk. In general, supply chain robustness is the reliability rate multiplied by system resilience (Robustness Rate = Reliability Rate * Resilience Rate). Equation (8.1) evaluates a supply chain system's robustness.

$$\psi = \Omega * \varphi \tag{8.1}$$

$$\psi_{X(i,j)} = \left\{ \left(T^T - \left(f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{X(i,j)}} + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{X(i,j)}} \right) \right) \times \frac{1}{T^T} \right\} \times \frac{T^T + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{X(i,j)}} + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{X(i,j)}}}{T^T + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}D_{\mathrm{X}(i,j)}} + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{X(i,j)}} + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{X(i,j)}}}$$

when

$$T^T \le \left(f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\sigma_{X(i,j)}} + f_{\mathrm{X}(i,j)\sum_{j=1}^{J}\sum_{i=1}^{I}\varepsilon_{X(i,j)}} \right), \quad \psi_{X(i,j)} = \Omega_{\mathrm{X}(i,j)} = 0$$

where

$$\varepsilon_{\mathrm{X}(i,j)} = \begin{cases} if \;\; f_{\mu\,\mathrm{X}(i,j-1)} > f_{\mu\,\mathrm{X}(i,j)} \;, & f_{\mu\,\mathrm{X}(i,j-1)} - f_{\mu\,\mathrm{X}(i,j)} \\ 0 \;\; otherwise \end{cases}$$

(8.2)

where $\psi_{X(i,j)}$ is the robustness rate of entity type X number i in level number j, T^T represents the due time, $\sigma_{X(i,j)}$ is standard deviation (uncertainty) of entity type X number i in level number j, $\varepsilon_{X(i,j)}$ is the delay due to waiting for products to be received from previous entity type X number i in previous level number j-1, $\mu_{X(i,j)}$ is the mean time of entity type X number i in level number j to complete the required job, $D_{X(i,j)}$ represents the recovery time of entity type X number i in level number j to complete the required job, X represents the type of entity, which can be route (R), factory (F), or supplier (S), i represents entity number, and j represents level number.

8.4.1 Numerical Example

This example consists of a supply chain system that has two levels and three entities, as shown in Figure 8.2. The entities are supplier ($S_{1,1} = N(30,3^2)$), route ($R_{2,1} = N(25,4^2)$), and factory ($F_{2,1} = N(32,3^2)$). The due date to complete one batch is 80 hours ($T^T = 80$). The objective of this example is to measure the resilience rate using the developed measure. Two scenarios are applied: no disruption, and a disruption that takes 168 hours (hr.) (two weeks if the work per day is assumed to be 12 hours) to recover.

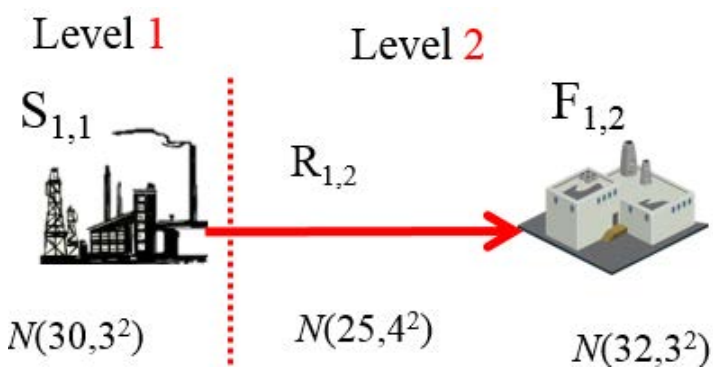

Figure 8.2. Example supply chain system

Step 1. Calculate the cumulative standard deviations (uncertainty) of the disruption time of each entity's distribution function. Since in this example all entities are assumed to be normally distributed, their sum is also normally distributed.

$$f_{S(1,1)\sum_{j=1}^{1}\sum_{i=1}^{1}\sigma_{1,1}} = \sqrt{3^2} = 3$$

$$f_{R(2,1)\sum_{j=1}^{2}\sum_{i=1}^{1}\sigma_{i,j}} = \sqrt{3^2+4^2} = 5\,\text{hr.}$$

$$f_{F(2,1)\sum_{j=1}^{2}\sum_{i=1}^{1}\sigma_{i,j}} = \sqrt{3^2+4^2+3^2} = 5.8310\,\text{hr.}$$

Step 2. Calculate the cumulative delay function associated with the time that entity *i* spent waiting for products from the previous factory in the previous level *j-1*.

$$f_{S(1,1)\sum_{j=1}^{1}\sum_{i=1}^{1}\varepsilon_{i,j}} = 0$$

$$f_{R(2,1)\sum_{j=1}^{2}\sum_{i=1}^{1}\varepsilon_{i,j}} = 0 + (30-25) = 5$$

$$f_{F(2,1)\sum_{j=1}^{2}\sum_{i=1}^{1}\varepsilon_{i,j}} = 0 + (30-25) + 0 = 5$$

Step 3. Calculate for each entity the cumulative recovery time function when disruption occurs.

$$f_{S(1,1)\sum_{j=1}^{1}\sum_{i=1}^{1}D_{i,j}} = 168\,\text{hr.}$$

$$f_{R(2,1)\sum_{j=1}^{2}\sum_{i=1}^{1}D_{i,j}} = 168+0=168\,\text{hr.}$$

$$f_{F(2,1)\sum_{j=1}^{2}\sum_{i=1}^{1}D_{i,j}} = 168+0+0=168\,\text{hr.}$$

Step 4. Calculate the reliability rate of each entity in the system using equation (6.2).

$$\Omega_{S(1,1)} = \left(80-(3+0)\right)\times\frac{1}{80} = 0.9625$$

$$\Omega_{R(2,1)} = \left(80-(5+5)\right)\times\frac{1}{80} = 0.8750$$

$$\Omega_{F(2,1)} = \left(80-(5.8310+5)\right)\times\frac{1}{80} = 0.8646$$

Step 5. Calculate the overall system resilience rate using equation (7.2).

When there is no disruption:

$$f_{F(2,1)\sum_{j=1}^{2}\sum_{i=1}^{1}D_{i,j}} = 0+0+0=0\,\text{hr.}$$

$$\varphi = \frac{80+5.8310+5}{80+0+5.8310+5} = 1$$

When there is disruption of two weeks:

$$f_{F(2,1)\sum_{j=1}^{2}\sum_{i=1}^{1}D_{i,j}} = 168+0+0=168\,\text{hr.}$$

$$\varphi = \frac{80+5.8310+5}{80+168+5.8310+5} = 0.3509$$

Step 6. Calculate the overall system robustness rate using equation (8.2).

When there is no disruption:

$$\psi = \left\{ \left(80 - (5.8310 + 5)\right) \times \frac{1}{80} \right\} \times \frac{80 + 5.8310 + 5}{80 + 0 + 5.8310 + 5} = 0.8646$$

When there is disruption and a two-week takes recovery period:

$$\psi = \left\{ \left(80 - (5.8310 + 5)\right) \times \frac{1}{80} \right\} \times \frac{80 + 5.8310 + 5}{80 + 168 + 5.8310 + 5} = 0.3034$$

In conclusion, as shown in Figure 8.3, robustness of this supply chain system is 86.46% when system resilience is 100% and the reliability rate 86.46%. In the second scenario, when there is a disruption and the system takes two weeks to recover, system robustness is 30.34%, system resilience is 35.09%, and the system reliability rate is 86.46%. In the next section, a complex SCS case study is evaluated using a developed measurement to demonstrate the efficacy of the proposed models in measuring reliability, resilience, and robustness of any factory-to-factory SCS.

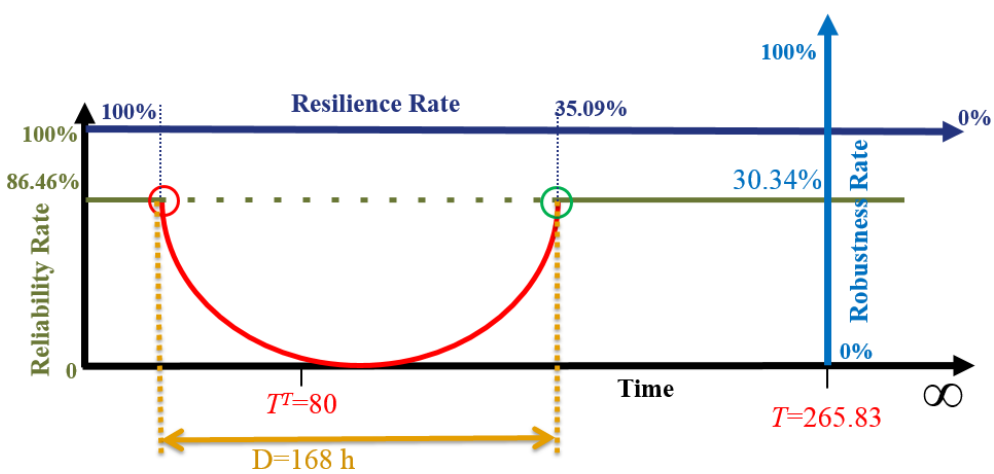

Figure 8.3. SCS reliability, resilience, and robustness rates during disruption

8.5 Case Study

This case study demonstrates the efficacy of the developed reliability, resilience, and robustness measures involving a complex SCS consisting of factories that are connected in parallel and series. This supply chain system consists of five levels and contains 17 entities, which are eight factories and nine routes, as shown in Figure 8.4. In this SCS, factories cannot start the job until all required parts are received from factories in the previous level. For example, factory $F_{1,4}$ will not start until it receives the required parts from factory $F_{1,3}$ and factory $F_{2,3}$.

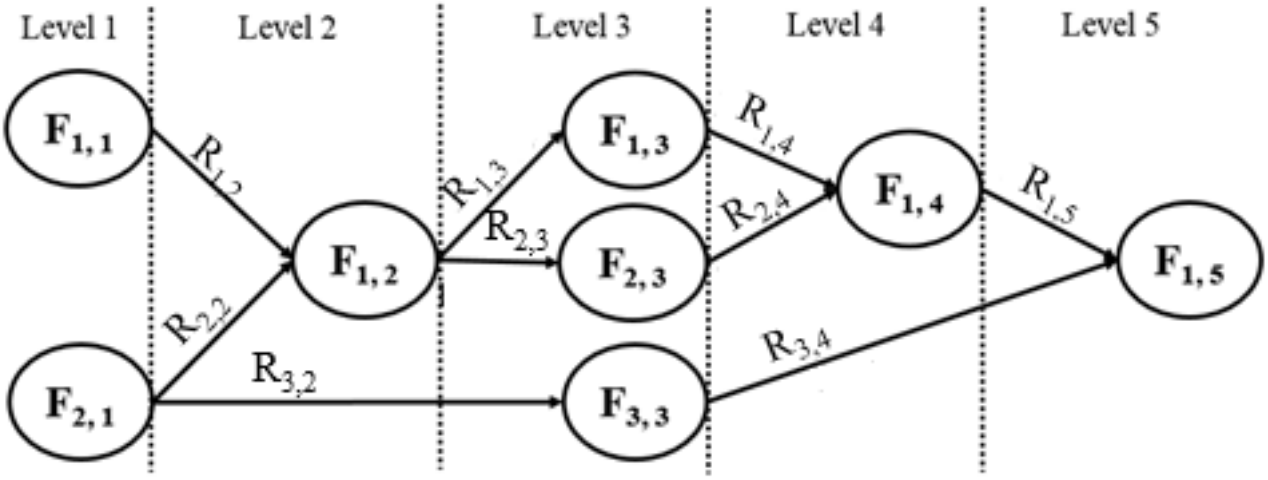

Figure 8.4. Case study complex supply chain system

For purposes of this case study, the collected data (design parameters) is assumed to be normally distributed, and the means and standard deviations are shown in Table 8.1. Two scenarios have been applied to this case study:

- Scenario 1: No disruption.
- Scenario 2: A disruption requiring 45 days to recover (45 days *24 hours = 1,080 hours of disruption)

To solve this case study, the supply chain was modeled with mathematical simulation using MATLAB R2013a. Also, measurement models were applied to measure system reliability, resilience, and robustness. Output from these simulation models is shown in Tables 8.2 and 8.3.

TABLE 8.1

CASE STUDY DESIGN PARAMETERS

Entity (i,j)	**Mean Time (μ) (hr)**	**Time variation (σ) (hr)**
Factory 1 ($F_{1,1}$)	183	34
Factory 2 ($F_{2,1}$)	276	41
Factory 3 ($F_{1,2}$)	269	22
Factory 4 ($F_{1,3}$)	274	27
Factory 5 ($F_{2,3}$)	261	23
Factory 6 ($F_{3,3}$)	266	30
Factory 7 ($F_{1,4}$)	195	39
Factory 8 ($F_{1,5}$)	288	32
Route 1 ($R_{(1,2)}$)	201	25
Route 2 ($R_{(2,1)}$)	277	34
Route 3 ($R_{(3,1)}$)	182	29
Route 4 ($R_{(1,3)}$)	211	39
Route 5 ($R_{(2,3)}$)	272	50
Route 6 ($R_{(1,4)}$)	190	41
Route 7 ($R_{(2,4)}$)	280	37
Route 8 ($R_{(3,4)}$)	195	29
Route 9 ($R_{(1,5)}$)	212	40

TABLE 8.2

SYSTEM PERFORMANCE WHEN NO DISRUPTION OCCURRED

1	2	3	4	5	6
Entity (*i*,*j*)	**Total Mean Time (*μ*) (hr)**	**Delay (*ε*) (hr)**	**Reliability Rate (Ω) (%)**	**Resilience Rate (*φ*) (%)**	**Robustness Rate (*ψ*) (%)**
$F_{1,1}$	217.12	33.92	98.54	100	98.54
$F_{2,1}$	316.92	40.97	98.24	100	98.24
$F_{1,2}$	887.39	65.5	97.19	100	97.19
$F_{1,3}$	1,447.81	140.73	93.96	100	93.96
$F_{2,3}$	1,453.37	98.67	95.77	100	95.77
$F_{3,3}$	876.4	152.38	93.46	100	93.46
$F_{1,4}$	2,029.6	199.86	91.42	100	91.42
$F_{1,5}$	2,542.42	212.62	90.87	100	90.87
$R_{(1,2)}$	426.24	42.14	98.19	100	98.19
$R_{(2,1)}$	606.05	53.16	97.72	100	97.72
$R_{(3,1)}$	602.16	144.09	93.82	100	93.82
$R_{(1,3)}$	1,168.53	135.57	94.18	100	94.18
$R_{(2,3)}$	1,178.03	84.22	96.39	100	96.39
$R_{(1,4)}$	1,732.41	235.22	89.9	100	89.9
$R_{(2,4)}$	1,741.39	106.66	95.42	100	95.42
$R_{(3,4)}$	1,149.03	230.08	90.13	100	90.13
$R_{(1,5)}$	2,249.48	207.75	91.08	100	91.08

TABLE 8.3

SYSTEM PERFORMANCE WHEN 1,080 HOURS OF DISRUPTION OCCURRED

1	2	3	4	5	6
Entity (i,j)	**Total Mean Time (μ) (hr)**	**Delay (ε) (hr)**	**Reliability Rate (Ω) (%)**	**Resilience Rate (φ) (%)**	**Robustness Rate (ψ) (%)**
$F_{1,1}$	217.07	33.99	98.54	100	98.54
$F_{2,1}$	316.86	41.03	98.24	100	98.24
$F_{1,2}$	887.3	65.47	97.19	100	97.19
$F_{1,3}$	1,447.42	140.4	93.97	100	93.97
$F_{2,3}$	1,452.95	98.3	95.78	100	95.78
$F_{3,3}$	1,956.33	1,232.50	93.46	69.68	65.12
$F_{1,4}$	3,109.62	1,171.42	91.42	83.5	76.33
$F_{1,5}$	3,622.39	1,292.60	90.87	70.19	63.78
$R_{(1,2)}$	426.35	42.25	98.19	100	98.19
$R_{(2,1)}$	605.96	53.22	97.72	100	97.72
$R_{(3,1)}$	601.87	144.1	93.82	100	93.82
$R_{(1,3)}$	1,168.24	135.3	94.19	100	94.19
$R_{(2,3)}$	1,177.69	84.05	96.39	100	96.39
$R_{(1,4)}$	1,731.97	234.9	89.92	100	89.92
$R_{(2,4)}$	1,741.27	106.6	95.42	100	95.42
$R_{(3,4)}$	2,229.22	1,310.40	90.11	70.33	63.38
$R_{(1,5)}$	3,329.59	1,287.90	91.08	83.54	76.09

Table 8.2 illustrates the current state of the system and shows cycle time, delay time, reliability rate, resilience rate, and robustness rate when there is no disruption. The first column in this table is the number of factories and routes in the system, which identifies entity type and location. The second column shows the initial mean cycle time in factories during processing and routes during transportation to complete one batch. For example, the measured processing time to complete one batch in factory 4 ($F_{1,3}$) is 1,447.42 hours. Column three describes the calculated

system delay for completing one batch for each entity. Columns four, five, and six show the current reliability, resilience, and robustness rates at each factory and route. Factory 8 is the last factory in the system and hence the reliability, resilience, and robustness rates achieved by this factory are considered to be the system reliability, resilience, and robustness rates. Also, it can be seen that the SCS reliability, resilience, and robustness rates decrease monotonically when traversing from the input point to the output point within the system. To illustrate, the reliability rate for factory 1 is 98.54%, whereas the system (Factory 8) reliability rate is 90.87%. In summary, when there is no disruption, the system cycle time is 2,542.42 hours. The system delay is 212.62 hours, system reliability is 90.87%, system resilience is 100%, and system robustness is 90.87%.

On the other hand, Table 8.3 describes the system state when there is a disruption and a recovery time of 1,080 hours on factory 6. Here it can be seen that when there is a disruption in one of the entities, all factories and routes located after the disruption area are affected because the disrupted entity will act as the SCS bottleneck. Also, Table 8.3 illustrates that when there is a disruption, system cycle time and delay increase to 3,622.39, and 1,292.60 respectively. System reliability is 90.87%, system resilience is 70.19%, and system robustness is 63.78%. Improvements on the overall SCS can be determined by implementing successive improvements to each entity in the supply chain. To improve system's reliability resilience and robustness rates, approaches discussed in the literature review can be implemented. For example, a parallel factory could be added.

8.6 Conclusion

This research addressed the need of introducing measures for determining reliability, robustness, and resilience of a supply chain system. In the design of supply chain systems, these measures will provide quantitative evaluation of the design effectiveness. The concept of

reliability, robustness, and resilience of supply chains and their measures allow designers to effectively design SCSs that can withstand disruptions and provide service at predisruption levels. Case studies were used to demonstrate the procedure for calculating reliability, resilience, and robustness for each of the entities and for the overall system in simple and complex supply chain systems. Case study results have indicated that the developed measures are capable of quantifying reliability, resilience, and robustness of all entities in the SCS and the overall system under any dynamic circumstances.

CHAPTER 9

CONCLUSIONS AND FUTURE WORK

9.1 Conclusion

This dissertation introduced the concept of service level rates, resilience, robustness, and reliability in supply chain systems. It also developed quantitative models for these concepts. An additional key aspect of this research is the application of these concepts to up-stream supply chain systems, in which there are factories supplying to other factories. In traditional supply chain research, most of the emphasis was on the down-stream aspects of supplying from factory to distributors and retailers. These quantitative models are useful in determining the efficiency and resilience of the systems. In addition, the research demonstrated the use of these quantitative models in design the supply chain.

In more detail, the goal this dissertation was to introduce innovative supply chain system performance measures and design methods to effectively address and analyze the challenges of SCS design under uncertainties and disruptions. In this research, nine research problems were defined, accomplished, and discussed in the seven main chapters. Chapter 2 reviewed the current related state-of-the-art methods of the proposed problems within the thrusts of this dissertation. Chapter 2 also reviewed current literature in the field of SCS uncertainty and risk factors, logistic qualities in the global SCS, quantitative SCS performance measures, and SCS design optimization.

Chapter 3 introduced the service level rate as a performance measure and studied different practices to improve the performance of supply chain systems. Furthermore, this chapter showed how a balanced system strategy and rescheduling the due date can affect performance of the supply chain. It also analyzed complex SCS characteristics.

Chapter 4 presented a novel robust design optimization methodology to derive designs of entity service level rates in order to satisfy the service level rate requirement of the system and ensure its robustness. Also, the chapter provided an analysis of the uncertainty impact introduced by system members on the robustness of overall SCS performance. It focused on maintaining SL rates at each step in the factory supply chain. It also showed that more value is added by using RDO in SCSs which includes systems in which one factory supplies to another factory.

Chapter 5 studied global supply chain risk and uncertainty on service performance cost in global supply chain systems. It discusses using RDO to promote the objective of reducing the service level cost. Also, global supply chain risks and uncertainty were studied along with SL rate cost in order to minimize the system-wide cost while maintaining customer satisfaction through SL requirements. This approach of designing SCSs helps to identify the entity that should be improved in order to minimize total cost while ensuring SL rate requirements. Results and analysis of this research emphasize that the proposed model can be used to redesign an upstream supply chain system whereby the system can be optimized to ensure service level rates, which in turn will lead to improved supply chain design planning and reduced costs. This research addressed the need of developing a methodology to design a cost-efficient supply chain system with the ability to highlight which factory and/or route in the system should be improved and how much this improvement will cost to satisfy overall SL rate requirements.

Chapter 6 introduced a novel measure to quantify the reliability rate of the overall supply chain system and the reliability of each member involved in the system. It also studied the effects of uncertainty and delays introduced by production and transportation on the reliability of the overall SCS. The chapter introduced an optimization approach to design a reliability rate of each

entity in the SCS such that the reliability rate requirement of the overall SCS is ensured. It also detailed an approach for calculating the SCS reliability rate.

Chapter 7 developed an evaluation model that has the ability to measure the resilience of any entity in the system and the resilience of the overall supply chain system. This chapter defined resilience within the context of an SCS and the relationship between various supply chain elements. It also addressed challenges due to the complexity in products, diversity of suppliers, end-customer geographic distribution, and intertwined industry relationships and processes among suppliers, manufacturers, distributors, retailers, and customer needs

The intent of Chapter 8 was to provide a study on the robustness of supply chain systems. Furthermore, a novel robustness measure able to evaluate SCS robustness and assist management in decision making was developed. This chapter illustrated how developed measurements models should be applied to a supply chain system. Methodologies to reduce the impact of uncertainty and increase SCS reliability, resiliency, and robustness were introduced.

9.2 Future Work

Future work from this research must continue to enhance optimization techniques. Other techniques such as genetic algorithms to determine faster solutions should be attempted. The concept of reliability, resiliency, and robustness can be extended to supplier selection and route selection. The same concepts that were applied in the factory-to-factory supply chain could be easily modified and applied to supplier reliability and resilience, and hence would be useful in determining the most resilient and robust supplier. Similarly, these concepts could be adapted to determine the most resilient routes.

The concepts of reliability, resilience, and robustness could also be applied to the analysis and evaluation of production planning and routing within factories. By applying all of these

techniques, a methodology for developing a cost-efficient robust and resilient dynamic real-time global supply chain system to overcome uncertainty impacts with the lowest cost possible could be identified.

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