DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

A DECISION SUPPORT SYSTEM FOR GLOBAL SUPPLY CHAIN RISK MANAGEMENT BY CONSIDERING PREMIUM FREIGHTS

by

Mualla Gonca AVCI

April, 2016
İZMİR

A DECISION SUPPORT SYSTEM FOR GLOBAL SUPPLY CHAIN RISK MANAGEMENT BY CONSIDERING PREMIUM FREIGHTS

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Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"A DECISION SUPPORT SYSTEM FOR GLOBAL SUPPLY CHAIN RISK MANAGEMENT BY CONSIDERING PREMIUM FREIGHTS"** completed by **MUALLA GONCA AVCI** under supervision of **ASSOC. PROF DR. HASAN SELİM** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

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A DECISION SUPPORT SYSTEM FOR GLOBAL SUPPLY CHAIN RISK MANAGEMENT BY CONSIDERING PREMIUM FREIGHTS

ABSTRACT

As a result of globalization, supply chains geographically spread on larger areas. This fact makes supply chains more vulnerable against supply chain risks. An adverse event affecting a supply chain partner may influence the entire supply chain, and even pose a threat on the competitive advantage of the supply chain. In this context, a decision support system (DSS) is developed for supply chain risk management (SCRM) in global supply chains. The proposed DSS covers all phases of SCRM, namely, risk identification, risk assessment, risk mitigation, risk monitoring and control phases. In the risk identification phase, the significant supply chain risks affecting material flow between supply chain agents are identified. In risk assessment phase, global supply chain is decomposed into material-level or product-level critical sub-networks according to the decision maker's preference by using TOPSIS. In the risk mitigation phase, the best parameter values for risk mitigation strategies are determined by using a simulation-based optimization framework. In particular, a decomposition-based multi-objective differential evolution algorithm is developed for the optimization phase of the framework. In the risk monitoring and control phase, supply chain performance is monitored continuously, and the DSS is re-implemented if it is needed.

The proposed DSS is implemented to an automotive supply chain spread on Europe. The DSS is employed to inbound and outbound risk management cases. The results obtained for both cases are presented in comparison with the results obtained from non-dominated sorting genetic algorithm-II (NSGA-II) and the current operating condition of the supply chain. The results reveal that the proposed DSS suggest better risk management solutions for both cases.

Keywords: Supply chain risk management, decision support system, premium freight, TOPSIS, simulation-based optimization

KÜRESEL TEDARİK ZİNCİRİ RİSK YÖNETİMİ İÇİN ACİL SEVKİYATLARI DİKKATE ALAN BİR KARAR DESTEK SİSTEMİ

ÖZ

Küreselleşmenin sonucu olarak, tedarik zincirleri daha geniş alanlara yayılmaya başlamıştır. Bu durum, tedarik zincirlerini risklere karşı daha korunmasız hale getirmektedir. Bir tedarik zinciri üyesini etkileyen olumsuz bir olay tüm tedarik zincirini etkilemekte, hatta tedarik zincirinin rekabet gücü için bir tehdit unsuru oluşturabilmektedir. Bu bağlamda, küresel tedarik zincirinde risk yönetimi (TZRY) için acil sevkiyatları dikkate alan bir karar destek sistemi (KDS) geliştirilmiştir. Önerilen KDS TZRY'nin risklerin belirlenmesi, risk değerleme, risk azaltma, risk izleme ve kontrol işlemlerinden aşamalarını kapsamaktadır. Risklerin belirlenmesi, tedarik zinciri üyeleri arasındaki malzeme akışını etkileyen dikkate değer tedarik zinciri riskleri belirlenmiştir. Risk değerleme aşamasında, küresel tedarik zinciri TOPSIS metodu kullanılarak karar vericilerin tercihlerine göre malzeme veya ürün seviyesinde kritik alt ağlara ayrıştırılmıştır. Risk azaltma aşamasında ise, benzetim tabanlı optimizasyon kullanılarak risk azaltma stratejileri için en iyi parametre değerleri belirlenmiştir. Özellikle, optimizasyon aşaması için ayrıştırma temelli bir çok amaçlı diferansiyel evrim algoritması geliştirilmiştir. Risk izleme ve kontrol aşamalarında, tedarik zinciri performansı sürekli bir şekilde izlenmekte ve gerek görülmesi durumunda KDS tekrar uygulanmaktadır.

Önerilen KDS, Avrupa'ya yayılmış bir otomobil tedarik zincirinde hem iç hem de dış risk yönetimi durumları için uygulanmıştır. Tüm durumlar için önerilen KDS'den elde edilen sonuçlar, tedarik zincirinin mevcut durumuyla ve domine edilmemiş sıralamalı genetik algoritma-II'nin sonuçlarıyla karşılaştırılmıştır. Elde edilen sonuçlar, önerilen KDS'nin tüm durumlar için daha iyi risk yönetimi çözümleri sunduğunu ortaya koymaktadır.

Anahtar Kelimeler: Tedarik zinciri risk yönetimi, karar destek sistemi, acil sevkiyat, TOPSIS, benzetim tabanlı optimizasyon

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CHAPTER ONE
INTRODUCTION

1.1 Motivation

As a result of globalization and advances in communication technologies, today's supply chains physically spread on larger areas. This fact drives inter-firm competition into global scale. Consequently, supply chains adopt lean principles, and partners in supply chains become more connected to gain cost advantage. However, these strategies make supply chains more vulnerable in terms of supply chain risks. Today, an adverse event affecting a supply chain partner may influence the entire chain. Moreover, these events can pose a threat on competitive advantage of organizations. In this context, Hendricks and Singhal (2005) investigate the long-term stock price effects and equity risk effects of supply chain disruptions based on a sample of 827 disruption announcements made during 1989–2000. Stock price effects are examined starting one year before through two years after the disruption announcement date. Over this time period, the average abnormal stock returns of firms that experienced disruptions is nearly 40%. Therefore, supply chain risk management (SCRM) has gained importance in both industry and academia in the last decade. Nowadays, firms need to understand supply chain interdependencies, identify potential risk factors, their likelihood, effects and severities.

Supply chain risk can be defined as likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of a supply chain leading to operational, tactical, or strategic level failures or irregularities (Ho, Zheng, Yildiz, & Talluri, 2015). The effects of supply chain risks mainly become observable on the material, financial and information flows of supply chains. Material flow risks arisen from physical flows between supply chain agents are product and process design risks, production capacity risks, disruption risks, demand volatility, and new product adoptions. Financial flow risk involves the inability to settle payments and improper investment such as foreign exchange rate risks, and price changes for materials. The information flow risks are information inaccuracy, information system security and disruption, information outsourcing and intellectual property risks (Tang & Nurmaya Musa, 2011). The focus of this thesis is related to the material flow risks.

SCRM is an inter-organizational, collaborative effort utilizing quantitative and qualitative risk management methodologies to identify, assess, mitigate, and monitor supply chain risks (Ho et al., 2015). SCRM process is generally consists of risk identification, risk assessment, risk mitigation, risk monitoring and control phases. Risk identification phase involves identification of possible adverse events related to internal or external environment of supply chain. In risk assessment phase, the whole supply chain or a specific agent related to the supply chain is evaluated in terms of the identified supply chain risks. In risk mitigation phase, risk mitigation plans are developed to protect the supply chain from risks, respond to adverse events, and recover from the impact of adverse events. In risk monitoring and control phase, the performance of risk mitigation plan is monitored. Moreover, risk mitigation plan may be reviewed and updated in case of a change in supply chain management strategy or environment.

Global supply chain management involves coordination of multiple locations spread on a large geographical area and management of economical, cultural, and regulation differences among the companies. Due to the complex supply chain structures and interrelationships, holistically analyzing global supply chains in terms of risks is challenging. In fact, global supply chains can be investigated by decomposing them into sub-systems under several scales by using different viewpoints such as a geographical zone, a hazard level, a supplier group or a particular type of product. Then, risk management activities can proceed conveniently for the pre-specified critical sub-systems. Moreover, risk management in global supply chains should be flexible so that it can be adapted easily to rapid changes in supply chain environment and competition strategy. Furthermore, global SCRM should mainly rely on quantitative data to perform more objective and reliable risk analyses.

In this thesis, a decision support system (DSS) is developed for SCRM in global supply chains. The proposed DSS provides comprehensive decision support in SCRM, since it covers all phases of SCRM, namely, risk identification, risk assessment, risk mitigation, risk monitoring and control phases. In the risk identification phase, the significant supply chain risks affecting material flow between supply chain agents are identified. In risk assessment phase, global supply chain is decomposed into material-level or product-level critical sub-networks according to the decision maker's preference. In this study, the critical sub-networks are identified by utilizing TOPSIS with entropy weighting.

In risk mitigation phase, redundancy and flexibility strategies for risk mitigation are evaluated by using simulation model of the critical sub-network. In this study, holding safety stock and excess production are considered as redundancy strategies. Additionally, supplier's quantity flexibility is considered as the flexibility strategy. These strategies are considered in a combined manner and evaluated in terms of both efficiency and effectiveness under multi-objective setting. To measure the efficiency of these strategies, annual holding cost of the supply chain is calculated. In addition, premium freight ratio is used to measure the effectiveness of the strategies.

To determine the best parameter levels related to risk mitigation strategies, a multi-objective simulation-based optimization framework is developed. Simulation model of the critical sub-network constitutes the simulation phase of the framework. For the optimization phase of the framework, a decomposition-based multi-objective differential evolution algorithm (MODE/D) is proposed. To demonstrate the efficacy of the algorithm, the performance of the algorithm is evaluated in comparison with non-dominated sorting genetic algorithm II (NSGA-II).

In risk monitoring and control phase, performance of the risk mitigation strategies are continually monitored and reviewed. In case of a major change in supply chain environment or competitive strategy, risk identification, risk assessment, risk mitigation and risk monitoring and control phases can be reiterated.

1.2 Contributions of the Thesis

As SCRM is still an emerging research field, there was a lack of quantitative studies until the last decade. In the last decade, quantitatively modeling supply chain risks and considering risk issues and mitigation strategies in quantitative supply chain models become attractive research directions. In this context, recent quantitative SCRM studies (the papers published between 2010 and 2015) are reviewed in this thesis.

In related literature, majority of the studies solely focus on risk assessment or risk mitigation stages of SCRM. There exist a few studies in which supply chain risks are identified, assessed and mitigated in an integrated manner. There is a scarce of SCRM framework covering all phases of SCRM in integrated manner. In this thesis, a comprehensive DSS consisting of risk identification, risk assessment, risk mitigation, risk monitoring and control phases of SCRM is developed.

Majority of the SCRM studies consider total expected cost or total expected profit as performance measure, and there exist a number of studies considering risk measures. Furthermore, there exist a few studies considering both cost-related and risk-related measures for SCRM performance. In this thesis, total holding cost and premium freight ratio are considered under multi-objective setting to measure efficiency and effectiveness of SCRM, respectively. Furthermore, there exists no study considering premium freight as a performance measure in supply chain management. This thesis bridges this gap, since premium freight is utilized as an additional objective to the cost objective.

In the risk mitigation phase of the proposed DSS, MODE/D is developed to determine the best parameter levels for risk mitigation strategies in terms of efficiency and effectiveness objectives of SCRM. As the proposed algorithm is a multi-objective optimization algorithm, multiple Pareto-optimal solutions are obtained. In practice, these solutions can be interpreted as alternative SCRM solutions. By comparing these solutions, the managers can consider a broad decision spectrum and consequently take the advantage of more flexible decision making.

The proposed DSS is a reliable and realistic tool as it uses quantitative data in risk assessment and employs statistical risk models relying on real historical data in risk mitigation. Additionally, it is flexible in determining the focus of risk management (material-level or product-level), and can be reutilized in case of a change in supply chain management strategy or supply chain environment.

1.4 Organization of the Thesis

This thesis consists of five sections. The introduction is the first chapter. The remaining chapters are organized as in the following.

In Chapter 2, a review of quantitative SCRM studies published in the last decade is presented. In particular, the studies are classified according to the SCRM stages considered, modeling and solution approaches. Additionally, simulation-based optimization approaches in supply chain inventory management field are examined. Moreover, the studies considering expedited shipping are presented.

In Chapter 3, the proposed DSS for global SCRM is explained through risk identification, risk assessment, risk mitigation, and risk monitoring and control phases of SCRM. Particularly, MODE/D and NSGA-II utilized in risk mitigation phase of the proposed DSS are explained in detail.

In Chapter 4, implementation of the proposed DSS on a real-world automotive supply chain is presented. The DSS is implemented to inbound and outbound risk management cases. The results obtained for both cases are presented in comparison with the results obtained from NSGA-II and the current operating condition of the supply chain.

Chapter 5 is devoted to presentation of the concluding remarks, contributions of thesis, and suggestions for future research.

CHAPTER TWO
LITERATURE REVIEW ABOUT SUPPLY CHAIN RISK MANAGEMENT

2.1 Introduction

Supply chain risk management (SCRM) is still an emerging research field in which definitions of risk concepts, risk classifications, and risk mitigation strategies are still unclear. Accordingly, there are ongoing attempts in academia to enhance the theoretical understanding in SCRM. In this context, several conceptual and empirical studies are published in the last decade. Among the conceptual studies, Juttner, Peck, and Christopher (2003) define supply chain risk concepts, and classify supply chain risk sources, consequences, and mitigation strategies. Chopra and Sodhi (2004) categorize supply chain risks, risk drivers and risk mitigation strategies. Christopher and Peck (2004) categorize supply chain risks, define the “resilient supply chain” concept, and propose strategies to ensure supply chain resilience. Sheffi (2005) defines and explains the stages of supply chain disruptions, issues in supply chain vulnerability assessment, and the strategies for supply chain resilience. Tang (2006) classifies supply chain risks and risk mitigation strategies. Recently, Heckmann, Comes, and Nickel (2015) criticize the existing supply chain risk definitions, and explain core characteristics of supply chain risks and supply chain risk measures. For a comprehensive review about conceptual studies on SCRM, the reader may refer to Rao and Goldsby (2009) and Singhal, Agarwal, and Mittal (2011).

Moreover, there exist several empirical studies aimed at establishing relationships between supply chain risks and supply chain performance in SCRM field. Hendricks and Singhal (2005) investigate the long-term stock price effects and equity risk effects of supply chain disruptions. Wagner and Bode (2006) investigate the relationship between supply chain vulnerability and supply chain risk. Thun and Hoenig (2011) identify the supply chain risks in German automotive industry by analyzing their likelihood to occur and their potential impact on the supply chain, and investigate instruments for dealing with supply chain risks. Blome and Schoenherr (2011) investigate SCRM approaches of the companies in financial crises by a multiple case study approach. Cantor, Blackhurst, and Cortes (2014) examine the effects of individual's regulatory focus, level of risk, and the uncertainty of the supply chain disruption on the willingness to pursue a new disruption mitigation strategy. For a comprehensive review of empirical studies on SCRM, the reader may refer to Rao and Goldsby (2009) and Singhal et al. (2011).

Furthermore, several review papers aimed at structuring SCRM field are published in the last decade. These papers are reviewed in Section 2.2 of this thesis. Besides, the quantitative approaches to SCRM have gained importance in the last decade. In this context, the aim of this literature review is to provide a comprehensive review of the recent quantitative studies in SCRM field. A review of the quantitative studies published in SCRM field from 2010 to 2015 is presented in Section 2.3. Moreover, as a simulation-based optimization approach is proposed for risk mitigation phase of the DSS, simulation-based optimization approaches in supply chain inventory optimization field are reviewed in Section 2.3. Furthermore, as premium freights are considered in this thesis, the studies focused on expedited shipping are investigated in Section 2.4. Finally, concluding remarks about SCRM literature are provided in Section 2.5.

2.2 Review Studies about SCRM

There exist several literature review studies in SCRM. Among them, C. S. Tang (2006) provides the first comprehensive review about SCRM studies. He classifies SCRM articles according to four basic approaches in supply chain management, namely, supply management, demand management, product management, and information management. Additionally, he investigates various SCRM strategies in the literature.

Rao and Goldsby (2009) review SCRM literature through risk sources consisting of environmental, industrial, organizational, problem specific, and decision maker related factors. Vanany, Zailani, and Pujawan (2009) classify SCRM studies into five categories, namely, conceptual, descriptive, empirical, exploratory cross-sectional, and exploratory longitudinal. Moreover, they examine SCRM studies in terms of unit of analysis, industry sectors, and risk management strategies.

Singhal et al. (2011) investigate SCRM literature by considering research approaches and exploration of key risk issues. In terms of research approaches, the studies are categorized based on the nature of the study and research methods. By considering the key research issues, the studies are classified according to risk definition/classification criteria, risk issues related to structural elements of supply chain, and level of risk management implementation. Tang and Nurmaya Musa (2011) use citation/co-citation analysis to investigate structures and evolution of SCRM research. Moreover, they classify SCRM studies in terms of risks related to material flow, financial flow and information flow in supply chains.

Colicchia and Strozzi (2012) conduct citation network analysis to examine the evolution of SCRM field and identify the critical studies on SCRM theory building. Sodhi, Son, and Tang (2012) review SCRM literature and survey two focus groups of supply chain researchers with open ended questions to clarify the perspectives of researchers. Rangel, de Oliveira, and Leite (2014) review SCRM literature through 16 risk classifications. They relate the risk classifications to the management processes in supply chain, namely, plan, source, make, deliver, and return.

Fahimnia, Tang, Davarzani, and Sarkis (2015) use bibliometric and network analysis tools to identify the mature and the emergent research streams in SCRM. They identify key research clusters/topics, interrelationships, and research areas that have provided SCRM field with the foundational knowledge, concepts, theories, tools, and techniques. Heckmann et al. (2015) investigate SCRM literature in terms of risk definitions, core characteristics of risks, risk measures, modeling approaches, and solution techniques. Ho et al. (2015) review SCRM literature through risk definitions, risk types, risk factors, and risk management/mitigation strategies.

2.2 Quantitative Studies on SCRM

In contrast to the initial years in the development of SCRM field, percentage of quantitative studies on SCRM has been considerably increased in the last decade (Ho et al. (2015). In this context, the focus of this review is the quantitative studies on SCRM published between 2010 and 2015. In Table 2.1, recent studies on SCRM are summarized by considering commonly acknowledged stages of risk management, namely, risk identification, risk assessment, and risk mitigation.

Table 2.1 Classification of recent SCRM studies in terms of risk management stages

Author, Year	Risk Identification	Risk Assessment	Risk Mitigation
Kumar, Tiwari, and Babiceanu (2010)			✓
Tuncel and Alpan (2010)		✓	✓
Wang, Li, O'brien, and Li (2010)			✓
Datta and Christopher (2011)			✓
Gan, Sethi, and Yan (2011)			✓
Hofmann (2011)			✓
Liu and Nagurney (2011)			✓
Nair and Vidal (2011)		✓	
PrasannaVenkatesan and Kumanan (2011)			✓
Xia and Chen (2011)			✓
Xie, Yue, Wang, and Lai (2011)			✓
Adenso-Diaz, Mena, García-Carbajal, and Liechty (2012)		✓	
Bearzotti, Salomone, and Chiotti (2012)	✓	✓	✓
Carvalho, Barroso, Machado, Azevedo, and Cruz-Machado (2012)		✓	✓
Chen (2012)		✓	✓
Chen, Hao, Li, and Yiu (2012)			✓

Table 2.1 Classification of recent SCRM studies in terms of risk management stages (continued)

Author, Year	Risk Identification	Risk Assessment	Risk Mitigation
Chen, Mockus, Orcun, and Reklaitis (2012)			✓
Cheng, Yip, and Yeung (2012)		✓	
Diabat, Govindan, and Panicker (2012)	✓	✓	
Gu and Zhang (2012)			✓
Hahn and Kuhn (2012)		✓	✓
He and Zhao (2012)		✓	✓
Klibi and Martel (2012)	✓	✓	✓
Lei, Li, and Liu (2012)		✓	✓
Liu and Cruz (2012)		✓	
Ma, Liu, Li, and Yan (2012)			✓
Matsui (2012)			✓
Nakashima and Gupta (2012)			✓
Schmitt and Singh (2012)		✓	✓
Schmitt and Snyder (2012)			✓
Tang, Nurmaya Musa, and Li (2012)			✓
Xiaojun Wang, Chan, Yee, and Diaz-Rainey (2012)		✓	
Wang, Chu, Wang, and Kumakiri (2012)		✓	✓
Baghalian, Rezapour, and Farahani (2013)			✓
Chaudhuri, Mohanty, and Singh (2013)		✓	
Chen and Wu (2013)	✓	✓	
Ghadge, Dani, Chester, and Kalawsky (2013)	✓	✓	✓
Le, Arch-int, Nguyen, and Arch-int (2013)			✓
Li (2013)			✓
Samvedi, Jain, and Chan (2013)		✓	
Wu, Huang, Blackhurst, Zhang, and Wang (2013)		✓	

Table 2.1 Classification of recent SCRM studies in terms of risk management stages (continued)

Author, Year	Risk Identification	Risk Assessment	Risk Mitigation
Atwater, Gopalan, Lancioni, and Hunt (2014)		✓	
Bueno-Solano and Cedillo-Campos (2014)		✓	
Devika, Jafarian, Hassanzadeh, and Khodaverdi (2014)			✓
Han, Dong, and Sun (2014)			✓
Huang and Goetschalckx (2014)			✓
Manuj, Esper, and Stank (2014)			✓
Tomlin (2014)		✓	✓
Soleimani, Arshadi Khamseh, and Naderi (2014)			✓
Soni, Jain, and Kumar (2014)	✓	✓	
Wagner, Mizgier, and Arnez (2014)		✓	
Aqlan and Lam (2015a)	✓	✓	
Aqlan and Lam (2015b)	✓	✓	✓
Chu, You, Wassick, and Agarwal (2015)			✓
Cardoso, Paula Barbosa-Póvoa, Relvas, and Novais (2015)		✓	
Dominguez, Cannella, and Framinan (2015)		✓	
Govindan and Jepsen (2015)		✓	
Guertler and Spinler (2015)	✓	✓	
Rajesh and Ravi (2015)			✓
Sahay and Ierapetritou (2015)			✓
Simchi-Levi et al. (2015)	✓	✓	✓
Xu, Zuo, and Liu (2015)			✓

As one can infer from Table 2.1, the majority of recent SCRM studies focus on risk assessment or mitigation stages of SCRM. However, there is a scarce of integrated SCRM studies in which supply chain risks are identified, assessed and mitigated. In this thesis, a comprehensive decision support system (DSS) is developed to support decisions related to an integrated SCRM.

On the other hand, the SCRM studies can be categorized by considering the main flows in supply chain, namely, material, financial and information flows as in Tang and Nurmaya Musa (2011). The studies related to material flow risks focus on risks affecting physical movement of materials and products between supply chain agents. As this thesis focus on material flow risks in supply chain, the studies related to material flow risks are investigated in more detail subsequently.

The studies related to financial flow risks focus on supply chain risks such as bankruptcy, exchange rate, price and cost risks. Hofmann (2011) identifies the potentials of natural hedging approach in reducing supply chain vulnerability. Liu and Nagurney (2011) analyze the effects of foreign exchange risk and competition intensity on performance of companies with offshore-outsourcing activities. Liu and Cruz (2012) investigate the impact of financial risks on profitability, cash and credit transactions of supply chain agents. Matsui (2012) compares two cost-based transfer pricing methods, namely, full-cost and variable-cost pricing on profit. Hahn and Kuhn (2012) develop a robust optimization based framework for value-based performance and risk management in supply chains. For a more comprehensive review of SCRM studies related to financial flow risks, the reader may refer to Tang and Nurmaya Musa (2011) and Ho et al. (2015).

The studies related to information flow risks focus on supply chain risks, such as information accuracy, information system security, intellectual property and information outsourcing risks (Tang & Nurmaya Musa, 2011). Cheng et al. (2012) investigate effectiveness of "guanxi networks" (a relational approach in the Chinese business environment) in SCRM. Lei et al. (2012) study optimal supplier contracts under demand and cost disruptions with asymmetric information and demonstrate the impact of asymmetric disruption information on supply chain performance. Le et al. (2013) propose an algorithm for association rule hiding to mitigate knowledge leakage risk in retail supply chain collaboration. Han et al. (2014) propose a two-stage decision process with an unpayback deposit contract to mitigate distrust-induced risk in supply chain information sharing process. For a more comprehensive review of SCRM studies related to information flow risks, the reader may refer to Tang and Nurmaya Musa (2011) and Ho et al. (2015).

In Table 2.2, the recent SCRM studies related to material flow risks are summarized. The studies are classified into the modeling approaches. The categories for modeling approaches are determined as in (Peidro, Mula, Poler, & Lario, 2009). Then, the studies are classified by their solution approaches and performance measures (see Table 2.2).

Table 2.2 Classification of the recent SCRM studies in terms of modeling approaches, solution approaches and performance measures

Author, Year	Modeling approach	Solution approach	Performance measures
Wang et al. (2010)	Analytical models	Mathematical programming	Total cost
Gan et al. (2011)	Analytical models	Game theory	Total profits and risks of agents
Liu and Nagurney (2011)	Analytical models	Variational inequality	Total expected cost, total expected profit
Chen (2012)	Analytical models	Dynamic programming	Total profit
Chen et al. (2012)	Analytical models	Optimization via derivation	Total expected profit
Lei et al. (2012)	Analytical models	Optimization via derivation	Total profit
Ma et al. (2012)	Analytical models	Game theory	Total profit of manufacturer, CVaR of retailer
Schmitt and Snyder (2012)	Analytical models	Optimization via derivation	Total expected profit
Tang et al. (2012)	Analytical models	Optimization via derivation	Total expected profit

Table 2.2 Classification of the recent SCRM studies in terms of modeling approaches, solution approaches and performance measures (continued)

Author, Year	Modeling approach	Solution approach	Performance measures
Wang et al. (2012)	Analytical models	Optimization via derivation	Total expected profit
Baghalian et al. (2013)	Analytical models	Robust optimization	Total profit
Han et al. (2014)	Analytical models	Game theory	Total profits of agents
Huang and Goetschalckx (2014)	Analytical models	Branch-and-reduce algorithm	Total expected profit, standard deviation of profit
Soleimani et al. (2014)	Analytical models	Game theory	Total profits of agents
Cardoso et al. (2015)	Analytical models	Mixed integer linear programming	Expected net present value
Xu et al. (2015)	Analytical models	Game theory	Total profits of agents
Kumar et al. (2010)	Models based on artificial intelligence	Genetic algorithm, particle swarm optimization, artificial bee colony	Total cost with embedded risk
Datta and Christopher (2011)	Models based on artificial intelligence	Multi-agent based simulation	Service level, total inventory, average production run-length, average response time
Bearzotti et al. (2012)	Models based on artificial intelligence	Multi-agent based simulation	Order quantity and time variations
Wu et al. (2013)	Models based on artificial intelligence	Multi-agent based simulation	Stockout duration
Tuncel and Alpan (2010)	Simulation models	Petri nets	Total revenue, fill rate
Adenso-Diaz et al. (2012)	Simulation models	Monte-Carlo simulation	Supply chain reliability
Carvalho et al. (2012)	Simulation models	Discrete event system simulation	Total cost, lead time ratio
Klibi and Martel (2012)	Simulation models	Monte-Carlo simulation	Time to capacity recovery
Nakashima and Gupta (2012)	Simulation models	Discrete event system simulation	Total revenue

Table 2.2 Classification of the recent SCRM studies in terms of modeling approaches, solution approaches and performance measures (continued)

Author, Year	Modeling approach	Solution approach	Performance measures
Schmitt and Singh (2012)	Simulation models	Discrete event system simulation	Fill rate
Ghadge et al. (2013)	Simulation models	System dynamics simulation	Total cost, total delay
Bueno-Solano and Cedillo-Campos (2014)	Simulation models	System dynamics simulation	Total cost
Manuj et al. (2014)	Simulation models	Discrete event system simulation	Total revenue, total cost
Tomlin (2014)	Simulation models	Discrete event system simulation	Annual sales
Dominguez et al. (2015)	Simulation models	Discrete event system simulation	Bullwhip effect
Nair and Vidal (2011)	Hybrid Models	Multi-agent modeling, binomial logistic regression	Inventory levels, backorders and total costs
PrasannaVenkatesan and Kumanan (2011)	Hybrid models	Discrete event system simulation, particle swarm optimization	Total cost, supplier delivery reliability
Chen et al. (2012)	Hybrid models	Mixed integer linear programming, discrete event system simulation	Total cost
Devika et al. (2014)	Hybrid models	Discrete event system simulation, a multi-objective hybrid evolutionary approach	Bullwhip effect, net stock amplification
Chu et al. (2015)	Hybrid models	Multi-agent modeling, cutting plane algorithm	Inventory cost, fill rate
Sahay and Ierapetritou (2015)	Hybrid models	Two-stage stochastic programming, simulation modeling	Expected profit, total cost

As reported in Table 2.2, majority of the recent studies use analytical or simulation approaches. The studies using analytical approach model risks based on probability distributions and consider expected values as performance measures. However, analytical approaches with a number of impractical assumptions such as known probability distributions, linear relationships and static environment are not capable of sufficiently modeling complex real-world supply chains (Peidro et al., 2009; Singhal et al., 2011). Thus, simulation approaches are preferred in case of modeling complex supply chain systems with nonlinear relationships. Nevertheless, simulation approaches does not yield optimal solutions and reliability of the simulation results is a critical issue in obtaining accurate solutions.

Artificial intelligence based approaches consist of fuzzy approaches, multi-agent based modeling, and metaheuristic approaches. These approaches are favorable in cases of lack of risk data, decentralized supply chain structure, nonlinear and complex relationships, although they do not guarantee an optimal solution. Due to the advantageous characteristics of artificial intelligence approaches, there is a growing attention to the models based on artificial intelligence in SCRM field in recent years.

The hybrid models take the advantage of combining favorable characteristics of distinct modeling approaches. They consist of combination of artificial intelligence models with statistical models, combination of artificial intelligence models with mathematical programming, and simulation-based optimization. Simulation-based optimization is the most commonly used approach among the hybrid modeling studies in SCRM. In this study, simulation-based optimization approach is employed for mitigation of material flow risks in global supply chains. Hence, recent simulation-based optimization studies in supply chain inventory optimization field are investigated in the subsequent section.

By considering the performance measures in Table 2.2, it can be concluded that majority of the quantitative studies in the related field utilize total expected cost and profit as SCRM performance measure. Besides, the number of studies considering the risk measures such as supply chain reliability, CVaR, and bullwhip effect has increased recently. Furthermore, there exist a few study considering cost and risk measures under multi-objective setting in recent SCRM literature.

2.3 Simulation-based Optimization Approaches in Supply Chain Inventory Optimization

There exist several studies utilizing simulation-based optimization algorithms to solve supply chain inventory management problems. The reader may refer to (Jalali & Van Nieuwenhuyse, 2015) for a comprehensive review of simulation-based optimization approaches in inventory management field. In this section, simulation-based optimization approaches developed for supply chain inventory optimization are reviewed. The studies are categorized into four classes according to the simulation-based optimization approaches, namely, mathematical programming approaches, meta-modeling approaches, reinforcement learning approaches and metaheuristic approaches.

The studies employing mathematical programming develop simulation-based optimization frameworks in which optimization is inner loop and simulation is outer loop on the contrary of common simulation-based optimization perception in literature. Therefore, these frameworks can be named after "optimization-based simulation" frameworks, rather than simulation-based optimization frameworks. Among these studies, Nikolopoulou and Ierapetritou (2012) develop a hybrid simulation-based optimization approach by applying a mixed-integer linear programming formulation in the context of an agent based simulation. In the study, the material flow values are optimized from the solution of the optimization model and are used as input to the simulation model. By utilizing a simulation model, excess inventory and pending backorder levels at production sites are obtained and are fed into the optimization model. The approach is applied to an illustrative small scale supply chain management problem. In another work, Sahay and Ierapetritou (2015) propose a hybrid simulation-based optimization framework that uses two-stage stochastic programming in a rolling horizon framework. The framework enables taking optimum planning decisions considering demand uncertainty while managing risk. They apply the framework to two illustrative cases.

Meta-modeling approaches are utilized in building and optimizing meta-models that capture the relationships between decision variables and simulation output. Wan, Pekny, and Reklaitis (2005) extend the simulation-based optimization framework proposed by Jung, Blau, Pekny, Reklaitis, and Eversdyk (2004) by embedding least square support vector machine, Bayesian evidence framework, and design and analysis of computer experiment to reduce the computational effort. Schwartz, Wang, and Rivera (2006) present a simulation-based optimization framework involving simultaneous perturbation stochastic approximation to specify parameters of internal model control and model predictive control based decision policies for inventory management in supply chains. Merkuryeva, Merkuryev, and Vanmaele (2010) develop a hybrid simulation-based optimization algorithm consisting of a multi-objective genetic algorithm and a response surface-based local search algorithm to determine cycle lengths in cyclic production plan and order-up-to levels that optimizes total cost and fill rate. Devika et al. (2014) formulate bullwhip effect and net stock amplification by using response surface methodology, and optimize them by using a hybrid multi-objective algorithm consisting of electromagnetism mechanism algorithm and population-based simulated annealing.

Reinforcement learning algorithms are suitable for optimization of multi-agent based simulation models. Kwon, Im, and Lee (2007) propose a framework based on a combination of multi-agent and case-based reasoning approaches. By using the framework, three levels of collaboration among the partners, namely, autonomy, integration, and enhanced integration, are evaluated. The results reveal the importance of intensive collaboration for maximum performance. Chaharsooghi, Heydari, and Zegordi (2008) consider supply chain ordering management as a multi-agent system and formulate a reinforcement learning model to determine order quantities at minimum inventory holding and backordering costs. The model is applied to the Beer Game. The results obtained from the model are better than those of reinforcement learning with 1-1 rules and genetic algorithm (GA) based algorithms. Jiang and Sheng (2009) deal with dynamic inventory control in a supply chain with non-stationary customer demand. They propose a case-based reinforcement learning algorithm and implement it to a multi-agent model of a two-echelon supply chain. Kwak, Choi, Kim, and Kwon (2009) propose a situation-reactive vendor managed inventory approach that adapts replenishment quantity over time according to the changes in customer demand stream. To cope with the non-stationary demand situation, a retrospective action-reward learning model is developed in the study. Their approach is compared with two newsboy models and is found as more effective in terms of inventory costs. Kim, Kwon, and Kwak (2010) propose a multi-agent framework for the non-stationary inventory control problem with a service-level constraint in a multi-echelon supply chain. Within their framework, a cooperative demand estimation protocol and a distributed action-reward learning technique are developed. The experimental results reveal that the model outperforms the three comparison models with different safety lead times. Recently, Mortazavi, Arshadi Khamseh, and Azimi (2015) design an intelligent self-adaptive model for a four-echelon supply chain system subjected to fluctuations and stochastic customer demand. They apply a reinforcement learning algorithm to identify the order quantities with the lowest costs.

Metaheuristic approaches are widely utilized as simulation-based optimization tools in supply chain inventory management. Daniel and Rajendran (2005) propose a genetic algorithm for simulation-based optimization of the base-stock levels with the objective of total cost minimization. Koo, Adhitya, Srinivasan, and Karimi (2008) propose a simulation-based optimization framework to provide decision support for optimal refinery supply chain design and operation. They utilize non-dominated Sorting Genetic Algorithm-II to optimize profit margin and customer satisfaction index objectives. Silva, Sousa, Runkler, and Sá da Costa (2009) propose an ant colony optimization algorithm (ACO) for distributed optimization of delivery, scheduling and vehicle routing processes in a supply chain network. Taleizadeh, Niaki, Shafii, Meibodi, and Jabbarzadeh (2010) consider a single vendor-single buyer inventory problem and determine re-order point and order quantity of each product that minimize total cost by a particle swarm optimization (PSO) algorithm.

Shukla, Tiwari, Wan, and Shankar (2010) propose a hybrid approach incorporating simulation, Taguchi method, robust multiple non-linear regression analysis and Psychoclonal algorithm. Keskin, Melouk, and Meyer (2010) propose a simulation-based optimization approach incorporating a scatter search-based meta-heuristic to solve a generalized vendor selection problem that integrates vendor selection and inventory replenishment decisions of a firm. Kuo and Han (2011) apply bi-level linear programming for modeling decentralized decision in a supply chain, and develop a hybrid algorithm consisting of genetic algorithm (GA) and PSO. Sinha, Aditya, Tiwari, and Chan (2011) propose a simulation-based optimization algorithm consisting of multi-agent simulation and a Co-evolutionary PSO based on Cauchy distribution for resource allocation decisions in a petroleum supply chain. PrasannaVenkatesan and Kumanan (2011) utilize a multi-objective binary PSO algorithm for designing the supply chain sourcing strategy that minimizes the total cost and maximizes the supplier delivery reliability. Duan and Warren Liao (2013) determine optimal replenishment policies of capacitated supply chains operating under decentralized and centralized control strategies by using a hybrid algorithm consisting of differential evolution (DE), harmony search (HS), and Hooke and Jeeves (HJ) direct search. In another study, Duan and Liao (2013) utilize this hybrid algorithm to demonstrate the effectiveness of a new age-based replenishment policy for supply chain inventory optimization of highly perishable products. Tsai and Zheng (2013) utilize sample average approximation to determine the optimal setting of stocking levels to minimize the total inventory investment costs while satisfying the expected response time targets for each field depot in a multi-item, multi-echelon inventory system. Godichaud and Amodeo (2015) utilize SPEA-II for simulation-based optimization of order sizes in a closed loop supply chain. The objective functions are determined as average holding cost for each site and fill rate.

2.4 Expedited Shipping

Expedited shipping is a widely utilized contingency strategy in SCRM in practice. Expedited shipping is a fast transportation service alternative offered by logistic service providers in case of an urgent delivery requirement. It generally involves high costs as it is a premium service. Besides, it is beneficial in reducing inventory carrying costs and adding flexibility to production planning (Terry, 2012).

There exist a number of studies considering expedited shipping. Huggins and Olsen (2003) consider two stage supply chain in which upstream facility always meets the supply requests from downstream. If the upstream facility cannot meet the supply requests from inventory on hand, the shortage is filled by expedited shipping. Caggiano, Muckstadt, and Rappold (2006) develop an integrated real-time model for making repair and inventory allocation decisions in a two-echelon reparable service parts system by considering regular and expedited shipping options. Gupta and Weerawat (2006) compare three different mechanisms in supplier-manufacturer coordination by considering expedited shipping. Zhou and Chao (2010) develop optimal inventory policies for an infinite-horizon, N-stage, serial production/inventory system with two transportation modes, namely, regular shipping and expedited shipping.

However, there exist a few studies considering expedited shipping as a contingency strategy in SCRM. Levy (1995) conducts a case study and develops a simulation model to investigate the effects of demand related disruptions on expedited shipping costs, inventory levels and demand fulfillment. Qi and Lee (2015) adapt expedited shipping as a contingency strategy towards the supplier disruptions to the problem dealt with by Tomlin (2006). The problem is related to a firm that can source from two suppliers such that an unreliable supplier and a reliable but expensive supplier.

2.5 Conclusion

This chapter provides a comprehensive review of recent quantitative studies related to SCRM, as well as, studies related to the issues and methods covered in this thesis. The literature review about SCRM reveals that SCRM is still an emerging research field in which several conceptual and review papers published recently. Besides, there is a growing attempt of quantitatively modeling supply chain risks and considering risk issues and mitigation strategies in quantitative supply chain models. Accordingly, this thesis focuses on quantitative SCRM.

In this context, recent quantitative SCRM studies are reviewed thoroughly. Firstly, the studies are investigated through the risk management stages covered. It is concluded that the majority of the studies focus solely on risk assessment or risk mitigation stages of SCRM. There exist a few studies in which supply chain risks are identified, assessed and mitigated in an integrated manner. Therefore, a DSS for integrated SCRM is developed in this thesis to bridge this gap.

Secondly, the studies are classified into material flow risk, information flow risk and financial flow risk categories by considering the main flows in supply chain. The focus of this thesis is material flow risks in supply chain. Consequently, the studies related to material flow risks are examined through their modeling approaches, solution approaches and performance measures. The majority of the recent studies related to material flow risks utilize analytical or simulation approaches. As stated previously, due to their impractical assumptions, analytical approaches are inadequate to model complex real world supply chain systems realistically. Nevertheless, simulation approaches are more suitable to complex real world supply chain system modeling, as their capability of handling complex nonlinear relationships. However, simulation approaches do not guarantee optimal solutions, and reliability of the simulation results is a critical issue. Artificial intelligence based approaches are preferred in cases of lack of risk data, decentralized supply chain structure, nonlinear and complex relationships between supply chain agents. However, they do not guarantee an optimal solution. Hybrid models combine advantageous characteristics of distinct modeling approaches. Among the hybrid approaches implemented to SCRM, simulation-based optimization is the most commonly utilized approach.

Finally, the recent quantitative studies considering material flow risks are investigated in terms of performance measures taken into account. Majority of the studies consider total expected cost or total expected profit as performance measures, and there exist a number of studies considering risk measures. In fact, a few studies consider both efficiency and effectiveness measures for SCRM performance. To bridge this gap, in this thesis, total holding cost and premium freight ratio is considered to measure efficiency and effectiveness of SCRM, respectively.

In the risk mitigation phase of the proposed DSS, a simulation-based optimization approach is developed. Hence, in Section 2.3, simulation-based optimization approaches implemented to supply chain inventory optimization field are reviewed. The studies are classified into four categories according to the simulation-based optimization approaches utilized. Among the simulation-based optimization approaches utilized in related literature, reinforcement learning and metaheuristic approaches are the most commonly used approaches.

In reinforcement learning approaches, all possible actions and associated rewards should be predetermined. However, in case of optimization of continuous variables, such as safety stock levels and supplier flexibility, all actions cannot be predetermined in adequate precision. In this case, metaheuristic algorithms suitable for continuous solution space come into consideration. As the studies utilizing metaheuristic approaches are investigated through the performance measures, it can be asserted that majority of the studies consider total cost as single performance measure. However, multi-objective algorithms become more common in related literature recently. Accordingly, in this thesis, a multi-objective metaheuristic algorithm is proposed for simulation-based optimization.

As stated previously, premium freight ratio is considered a performance measure in this thesis. As premium freight is a variant of expedited shipping, the studies considering expedited shipping are investigated. Although expedited shipping is a widely utilized contingency strategy in industry, there exists limited attempt to quantitatively analyze supply chain performance in terms of expedited shipping. Furthermore, there exist only two studies relating expedited shipping to SCRM. To bridge this gap in the literature, premium freights considered in supply chain models, and premium freight ratio is utilized as a performance measure to assess effectiveness of SCRM.

CHAPTER THREE
THE PROPOSED DECISION SUPPORT SYSTEM FOR GLOBAL SUPPLY CHAIN RISK MANAGEMENT

3.1 Introduction

In this thesis, a DSS is developed to support supply chain inventory management decisions by considering premium freights and supply chain risk. The proposed DSS involves a risk assessment phase in which the supply chain is decomposed into material-level or product-level sub-networks according to the decision maker's preference. Afterwards, simulation models are developed for each critical sub-network to evaluate the performances of the risk mitigation strategies. In particular, redundancy and flexibility strategies are considered for risk mitigation in this study. Holding safety stock and excess production which is more than forecasted demand size are considered as redundancy strategies. Additionally, supplier's quantity flexibility is considered as the flexibility strategy. These strategies are used in a combined manner and evaluated in terms of both efficiency and effectiveness. To measure the efficiency of these strategies, annual holding cost of the supply chain is calculated. In addition, premium freight (PF) ratio is used to measure the effectiveness of the strategies.

Furthermore, a multi-objective simulation-based optimization algorithm is developed in this study to determine the best parameter levels for the risk mitigation strategies. For the optimization phase of the algorithm, a decomposition-based multi-objective differential evolution algorithm (MODE/D) is proposed. Moreover, to demonstrate the effectiveness of MODE/D, the performance of MODE/D is compared with the performance of NSGA-II which is widely utilized in the related literature.

The process flow diagram of the proposed DSS is illustrated in Figure 3.1. In subsequent sections, general process of the proposed DSS is explained through commonly acknowledged stages of risk management, namely, risk identification (see

Section 3.2), risk assessment (see Section 3.3), risk mitigation (see Section 3.4) and risk monitoring and control (see Section 3.5). In specific, MODE/D and NSGA-II algorithms utilized in this thesis are explained in Section 3.4. Finally, concluding remarks about the proposed DSS are provided in Section 3.6.

3.2 Risk Identification Phase

Firstly, the risks affecting supply and delivery processes of the supply chain are identified. These risks can be classified as inbound and outbound risks. The inbound risks are related to the supply-side adverse events such as supplier delivery delay, delivery quantity loss and supplier disruptions. The outbound risks are arisen from customer-side adverse events such as customer demand variability, product delivery delay and shifting customer demand. As stated previously, the proposed DSS has flexibility in focusing on the risks related to the inbound or outbound flows. In this context, inbound and/or outbound risks are quantified according to the preference of the user. In particular, the supply chain risks are quantified through statistical models developed by using past order, premium freight and customer sales data. Once the supply chain risks related to each agent are quantified, the most critical sub-network in terms of risk is identified by risk assessment stage of the proposed DSS.

3.3 Risk Assessment Phase

In this stage, the critical sub-network is identified through a risk assessment procedure. The critical sub-network may be related to a material or a product type. To identify the critical sub-network, the most critical material or product is determined through a risk assessment procedure. In this context, the criteria for risk assessment should be identified. In criteria identification, the adverse effects of risks related to the focal material or product and criticality of them should be considered. Hence, the risk assessment stage involves multi-criteria decision making. Therefore, utilization of a multi-criteria decision making technique in risk assessment stage is appropriate. TOPSIS (Hwang & Yoon, 1981) is a suitable technique for this stage as it ranks the alternatives according to their criticality.

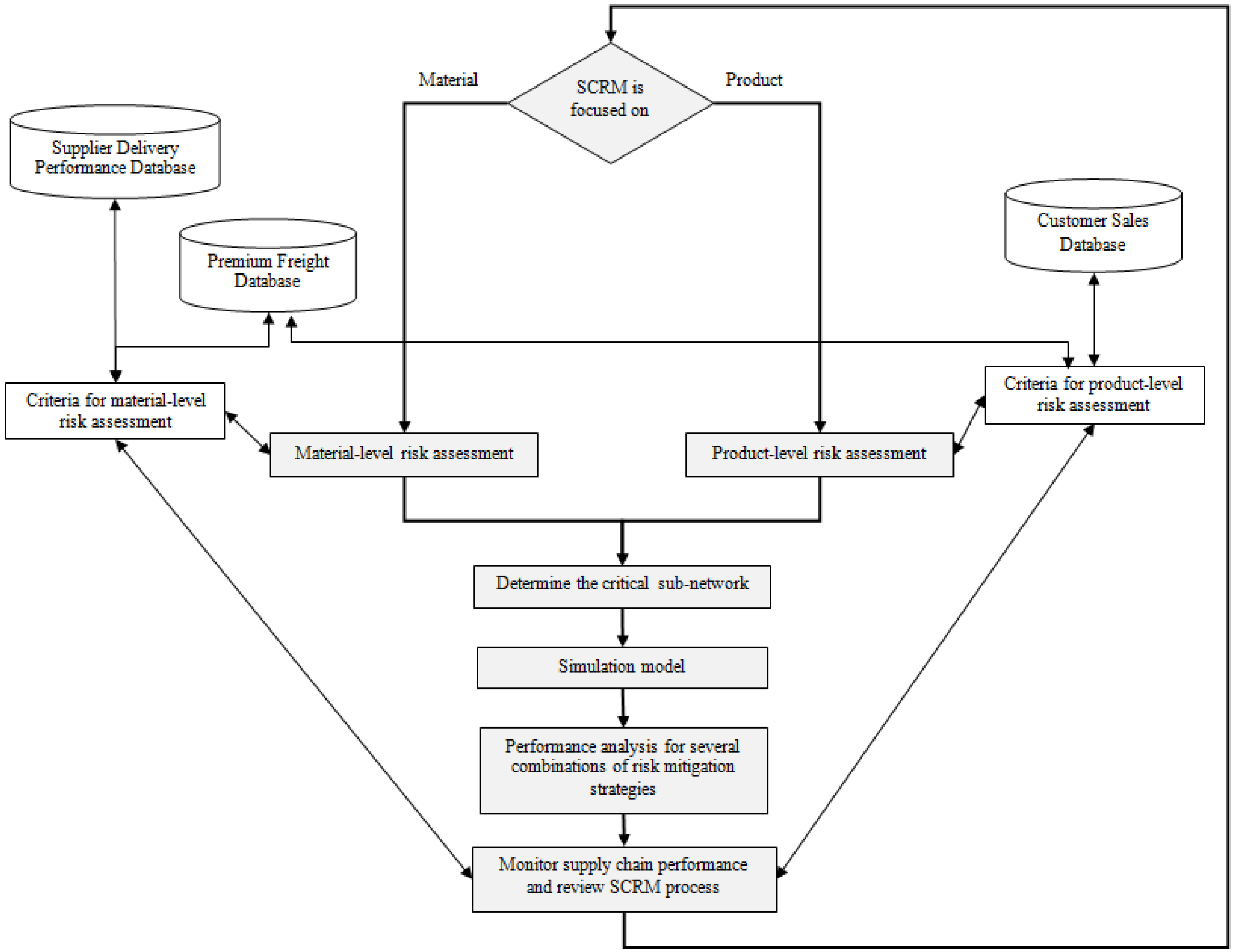

Figure 3.1 Process flow diagram of the proposed DSS

Assume that a multi-criteria decision making problem has m alternatives, $A_1, A_2, \dots, A_m$ and n criteria, $C_1, C_2, \dots, C_n$. All the ratings assigned to the alternatives with respect to each criterion form a decision matrix denoted by $D = (x_{ij})_{m\times n}$. Then, the ratings are normalized to form the normalized decision matrix.

In particular, in assessment of inbound or outbound flow risks, more than one decision matrices may come into consideration. As the suppliers and customers may be connected with more than one plant in the supply chain, more than one assessment for a criterion may come out. In this case, group decision making approaches can be used to merge the decision matrices into single decision matrix.

In this study, the criteria weights are determined by using entropy weighting method (Deng, Yeh, & Willis, 2000). The entropy value indicating the amount of information contained in each criterion is calculated as follows.

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{m} x_{ij} \ln(x_{ij}) \tag{3.1}$$

The degree of divergence (D_j) of the average intrinsic information contained by each criterion is calculated as follows.

$$D_j = 1 - e_j \tag{3.2}$$

As the degree of divergence represents divergence of the ratings in terms of criterion j, higher degree of divergence leads to higher criterion weight. In this sense, criteria weights are calculated as follows.

$$w_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \tag{3.3}$$

Aggregation procedure of TOPSIS is based on weighted Euclidian distances to negative and positive ideal solution.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} w_j (x_{ij} - p_j)^2} \tag{3.4}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} w_j (x_{ij} - n_j)^2} \tag{3.5}$$

where d_i^+ is the distance of alternative i to positive ideal solution, d_i^- is the distance of alternative i to negative ideal solution, p_j is the positive ideal value for criterion j, and n_j is the negative ideal value for criterion j.

The overall criticality index for alternative i is calculated as follows.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{3.6}$$

In the proposed DSS, the overall criticality index obtained by TOPSIS presents the criticality of material or product in terms of risk. The network related to the most critical material or product is specified as the critical sub-network. Afterwards, the critical sub-network is modeled to develop and evaluate risk mitigation strategies. Concept of the critical sub-network identification is illustrated in Figure 3.2.

An example supply chain system is demonstrated in Figure 3.2. In case of inbound flow analysis, the most critical material is identified as the material supplied by S2. Hence, the sub-network consisting of S2 and its vendors (P1, P2, and P3) is identified as the critical sub-network. Alternatively, in case of outbound flow analysis, the most critical product is identified as the product demanded by C3.

Therefore, the critical sub-network consists of the customer demanding the product (C3), the plant producing the product (P3) and the suppliers supplying the materials required for production of the product (S2 and S4).

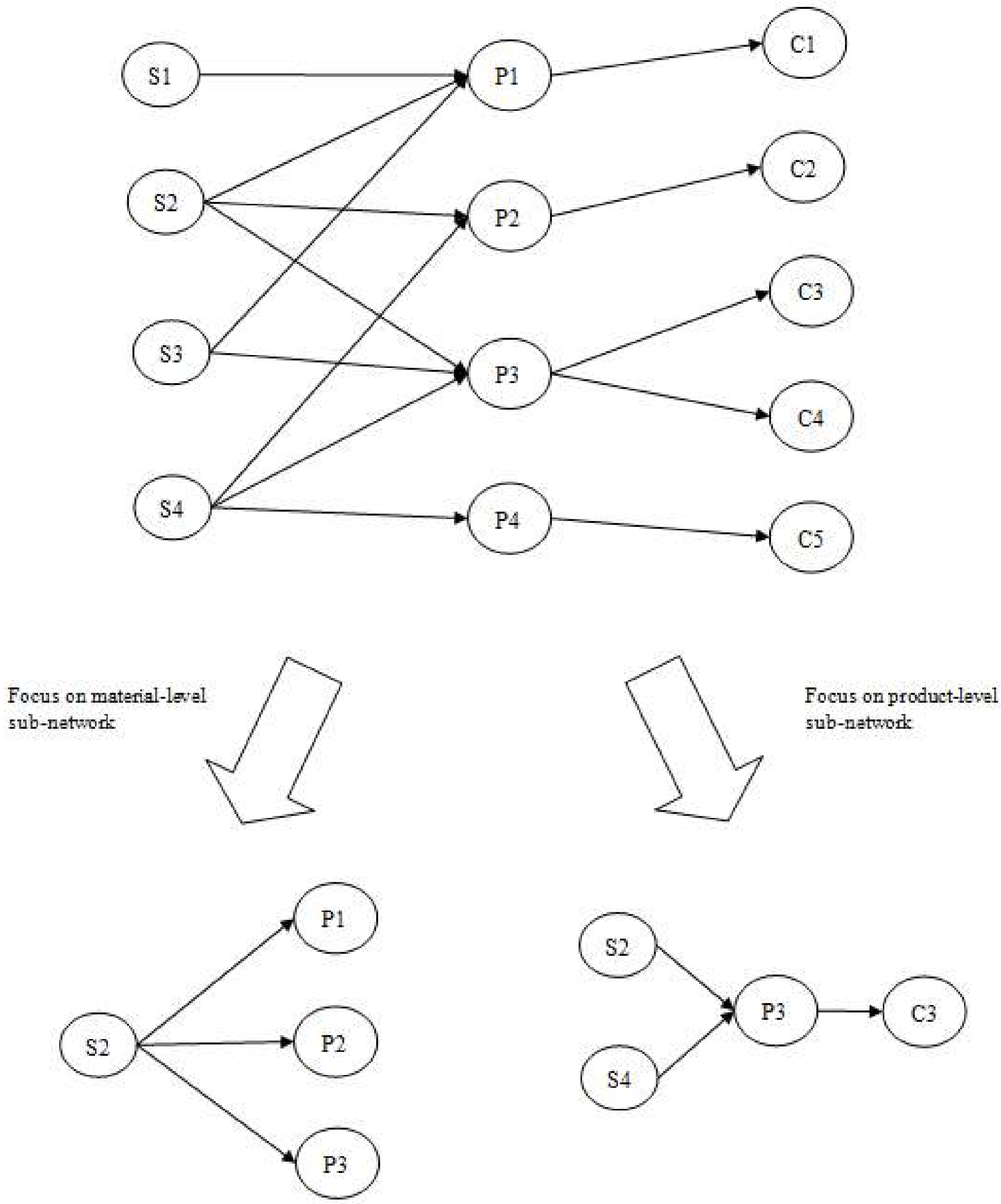

Figure 3.2 An example to critical sub-network identification

3.4 Risk Mitigation Phase

In this phase, a simulation model of the critical sub-network is developed. By utilizing the simulation model, a number of risk mitigation strategies are evaluated in terms of their effects on supply chain performance. In evaluation of the risk mitigation strategies, interrelationships between the strategies must be taken into account. For example, there is a strong relationship between redundancy and flexibility strategies. These strategies are effective in mitigating supply chain risks. However, combinations of these strategies often yield more effective and efficient risk mitigation due to their systemic effects. Herein, we cannot conclude that one strategy is superior to another strategy in terms of both effectiveness and efficiency. Therefore, in this study, these strategies is quantitatively described and evaluated by simulation experiments. The best combination of these strategies is determined in terms of effectiveness and efficiency. To evaluate the effectiveness and efficiency together, a multi-objective evaluation is required. Hence, both cost and premium freight performance are considered to measure efficiency and effectiveness together.

To determine the best parameter levels in terms of cost and premium freight performance for the risk mitigation strategies, a multi-objective simulation-based optimization framework is developed in this thesis. The parameters to be optimized are safety stock levels ($SS_1, SS_2, \ldots, SS_N$) and supplier flexibility levels ($F_1, F_2, \ldots, F_S$) of the agents in critical sub-network. The proposed framework consists of a simulation phase and an optimization phase (see Figure 3.3). In the simulation phase, supplier flexibility and safety stock levels generated by the optimization phase are evaluated in terms of total holding cost and PF ratio. The optimization phase uses output of the simulation phase in generating new safety stock and supplier flexibility levels.

The simulation and optimization phases of the proposed framework are explained in detail subsequently. Additionally, MODE/D, developed for the optimization phase of the proposed algorithm, and NSGA-II used for the performance comparison are explained thoroughly.

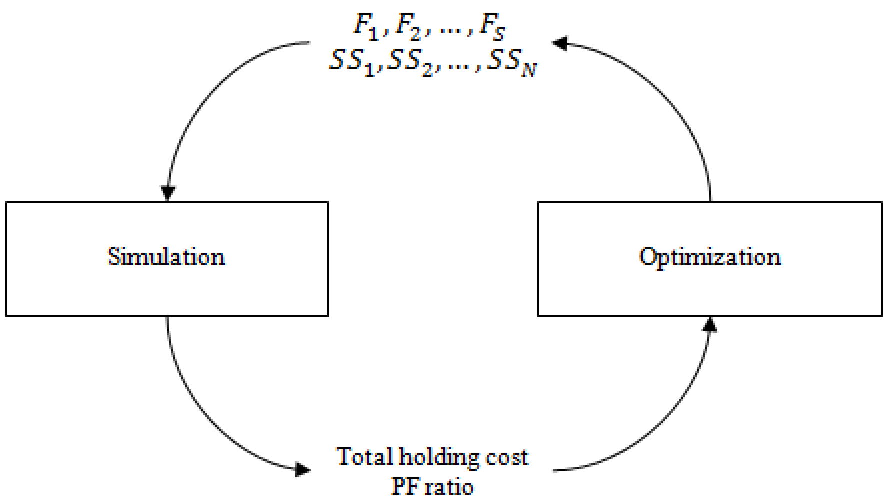

Figure 3.3 Main structure of the proposed simulation-based optimization framework

3.4.1 The Simulation Phase of the Proposed Algorithm

The simulation process starts with a vector containing safety stock levels and supplier flexibility level obtained from the optimization phase. In each day, plants make ordering and premium freight decisions independently by using the safety stock and supplier flexibility levels provided by the optimization phase. At the end of each day, the performance measures are recorded. This process continues until the simulation clock reaches to the predefined replication length (see Figure 3.4).

The performance measures considered in this thesis are “total holding cost” and “PF ratio”. Total holding cost is the summation of annualized total holding costs of the plants. PF ratio is the division of total regular orders to the premium freights made during the simulation. Performance values obtained from each replication are averaged and used as the system performance measures which are the input for the optimization phase.

As the supply chain system is highly complex and there exist uncertainties in the supply chain operations, reliability of the simulation experiments becomes more critical. In this context, a replication number control mechanism is embedded to the proposed simulation model. Particularly, this mechanism ensures that the performance values are at the desired precision. Herein, firstly, predefined number of replications (min rep no) are made before activating the mechanism. Afterwards, at the end of each replication, confidence intervals for each performance measure are calculated. If the half ranges of all confidence intervals are less than or equal to the prespecified maximum error rate (e_max), the simulation experiment is stopped. Otherwise, replications are continued until the prespecified maximum error rate is reached. Operation of the proposed replication number control mechanism is illustrated in Figure 3.4.

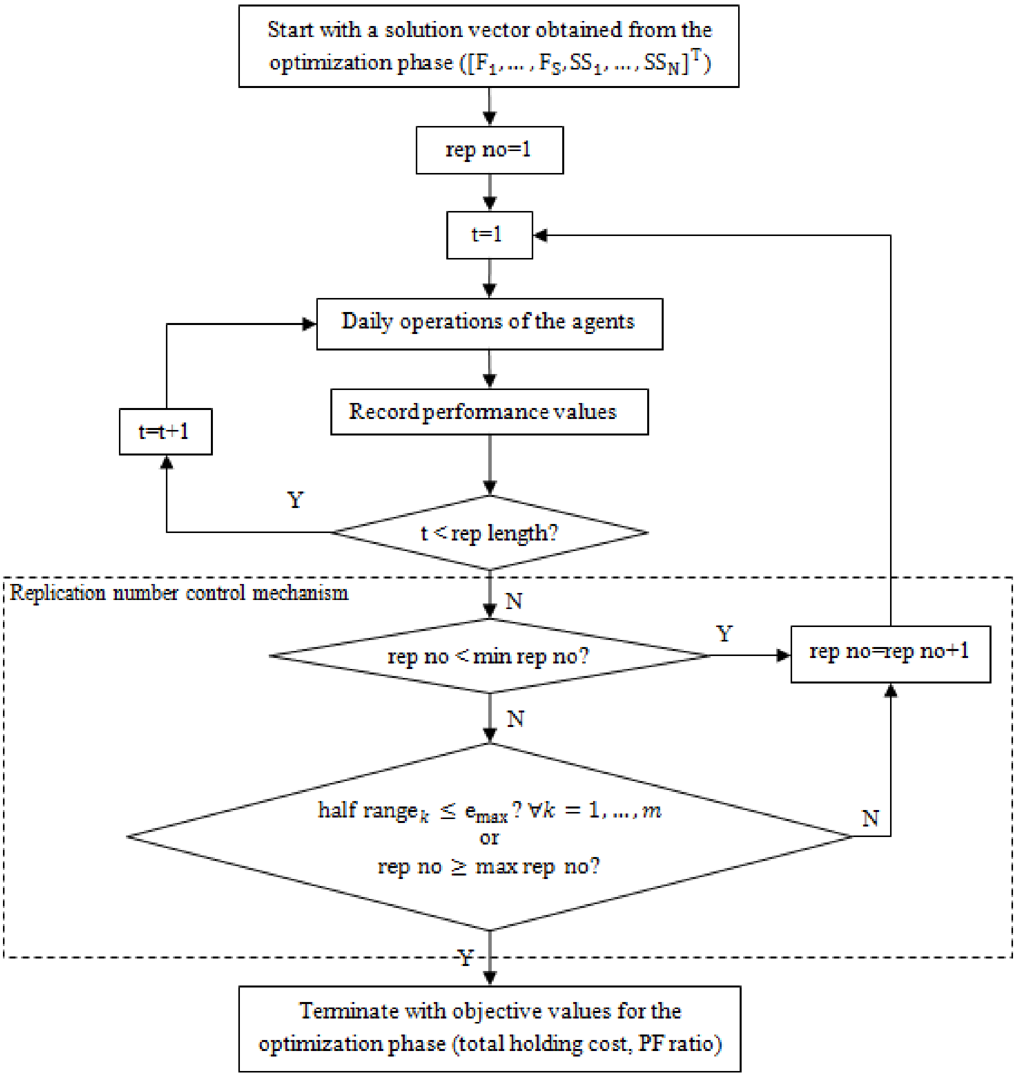

Figure 3.4 Flowchart of the simulation phase

3.4.2 Optimization Phase of the Proposed Algorithm

In optimization phase of the proposed algorithm, parameter values of the risk mitigation strategies are optimized under multi-objective setting. In this context, MODE/D is developed and compared with NSGA-II. MODE/D uses the output of the simulation phase as the objective function values of the solution vector, and generates new solution vectors to be evaluated by the simulation phase (see Figure 3.3). Subsequently, MODE/D and NSGA-II are explained in detail.

3.4.2.1 Decomposition-based Multi-Objective Differential Evolution Algorithm

In this thesis, a MODE/D is developed for the optimization phase of the proposed framework. Main structure of the proposed algorithm is inspired by multi-objective evolutionary algorithm based on decomposition (MOEA/D) proposed by Qingfu and Hui (2007). MOEA/D decomposes the multi-objective optimization problem into a number of scalar optimization sub-problems. The objective of each sub-problem is a weighted aggregation of individual objectives. Each sub-problem is simultaneously optimized by using the information from its neighborhood sub-problems. Neighborhood relations between sub-problems are defined by Euclidian distances between objective weight vectors associated with the sub-problems. For each sub-problem, the algorithm generates a new solution by using genetic operators and replaces the current solution with the new solution if the new solution has better fitness value in terms of the objective function of the sub-problem.

In real valued evolutionary algorithms, mutation is accomplished by randomly generated additive increments. However, it is challenging to adapt these increments to the natural scaling of the problems. Among the evolutionary algorithms, DE proposed by Storn and Price (1997) differs markedly in consideration of the fact that it mutates the base vectors with scaled population-derived difference vectors. As generations pass, these differences tend to adapt to the natural scaling of the problem. Consequently, there is no need to specify or adapt an absolute step size for each variable over generations (Das & Suganthan, 2011). Due to the aforementioned characteristics, DE operators are utilized in this study for the proposed algorithm.

A multi-objective optimization problem can be formulated as in the following.

$$\begin{aligned} &\text{minimize } F(x) = [f_1(x), \dots, f_m(x)]^T \\ &\text{subject to } x \in \Omega \end{aligned} \tag{3.7}$$

where Ω is the decision space, and $x \in \Omega$ is a decision vector. $F(x)$ consists of m objective functions $f_i: \Omega \rightarrow R^m$, $i = 1, \dots, m$, where R^m is the objective space. As the objectives generally conflict with each other, there is no solution that optimizes all the objectives simultaneously in the decision space. In other words, improvement of an objective may lead to deterioration of other objective. In this sense, the best trade-off solutions are defined as *Pareto optimal solutions* (Zhou et al., 2011).

As stated previously, the proposed algorithm decomposes the multi-objective optimization problem into a set of scalar optimization sub-problems. In this study, weighted Tchebycheff scalarizing function (Jaszkiewicz & Branke, 2008) is used for decomposition.

Let $\lambda = [\lambda_1, \dots, \lambda_m]^T$ be weight vector of a sub-problem and $z^* = [z_1^*, \dots, z_m^*]^T$ be a reference point. Then, objective function of a sub-problem is defined as follows.

$$g(x|\lambda, z^*) = \max_i [\lambda_i |f_i(x) - z_i^*|] \tag{3.8}$$

As objective functions may have different magnitudes, they should be scaled to a uniform, dimensionless scale. Therefore, normalized objective functions are used (see Eq. 3.9).

$$g(x|\lambda, z^*) = \max_i \left[\lambda_i \frac{|f_i(x) - z_i^*|}{z_i^{nad} - z_i^{**}}\right] \tag{3.9}$$

where $z^{nad} = [z_1^{nad}, \dots, z_m^{nad}]^T$ is a nadir point and $z^{**} = [z_1^{**}, \dots, z_m^{**}]^T$ is a utopian point.

MODE/D decomposes the multi-objective optimization problem into *NP* sub-problems using evenly distributed weight vectors $\lambda^1, \dots, \lambda^{NP}$. The individual weight values in weight vectors are controlled by parameter *H* as in the following.

$$\left[\frac{0}{H}, \frac{1}{H}, \dots, \frac{H}{H}\right]^T \tag{3.10}$$

Consequently, the number of weight vectors (NP) will be:

$$NP = C_{H+m-1}^{m-1} \tag{3.11}$$

As stated previously, MODE/D uses neighborhood information to optimize the sub-problems. Thus, in mutation phase, the individuals used to obtain the donor vector are selected randomly from the neighborhood of the current weight vector. The neighborhood of each weight vector is determined by using Euclidian distances between weight vectors. Afterwards, for each weight vector λ^j, a vector $B(j)$ containing the indices of *T* closest weight vectors to λ^j is constructed. On the other hand, the algorithm is allowed in selecting an individual from the outside of the neighborhood with a low probability $(1 - \delta)$ to enhance the exploration ability of the algorithm (Hui & Qingfu, 2009).

MODE/D begins with an initial population of *NP* and *D*-dimensional vectors generated from a uniform distribution within the range between lower bound (*LB*) and upper bound (*UB*) for each dimension. Then, the objective values of each individual are calculated. The non-dominated individuals are added to an external population (*EP*). Herein, *EP* is used to store the non-dominated individuals found during the search.

In MODE/D, DE/best/1/bin procedure is employed. In the mutation phase, three individuals are randomly selected either from $B(j)$ or from $[1, NP]$ according to the probability δ. Among these individuals, the individual with the best sub-problem objective value ($g(x|\lambda^j, z^*)$) is determined as the base vector. The difference between the other vectors is scaled by F, and added to the base vector. As a result, the donor vector (v^j) is obtained as defined in Eq. 3.12.

$$v^j = x^{best} + F(x^{r_1} - x^{r_2}) \tag{3.12}$$

By applying binary crossover with probability CR between donor vector (v^j) and target vector (x^j), the trial vector (u^j) is obtained.

In the selection phase, we use the constraint handling rules proposed by Deb (2000) as in the following.

- Any feasible solution is preferred to any infeasible solution.
- Among two feasible solutions, the one having better objective function value $g(x|\lambda, z^*)$ is preferred.
- Among two infeasible solutions, the one having smaller constraint violation ($cvio(x)$) is preferred.

At the end of each iteration, EP is updated. If the new individual is not dominated by any individual in EP, the new individual is added to EP, and the individuals dominated by the new individual are removed from EP. The algorithm operations proceed until a stopping criterion is met. Operations of the proposed algorithm are summarized in Figure 3.5.

```
Initialize algorithm parameters H,T,F,CR,δ
Set EP = ∅
For j = 1,…,NP
    Set B(j) = [j_1,…,j_T]     //where λ^{j_1},…,λ^{j_T} are T closest weight vectors
to λ^j
End For
Generate an initial population of NP individuals x^1,…,x^NP from
uniform  distribution within the range [LB,UB]
Calculate objective function values of each individual
Add the non-dominated individuals to EP
While Stopping criterion is not met
   For j = 1,…,NP
      If rand ∈ [0,1] ≤ δ
         Generate three mutually exclusive integers from B(j) randomly.
      Else
         Generate three mutually exclusive integers from the range
         [1,NP] randomly.
      End If
      Among the randomly generated indices, identify the best as the
      index yielded the best g(x|λ^j,z*) value and set r_1and r_2 at the
      other indices
      Generate a donor vector v^j (Eq. 3.12)
      For k = 1,…,D
         If rand ∈ [0,1] ≤ CR or j = j_rand
            u_k^j = v_k^j
         End If
      End For
      If cvio(u^j) = cvio(x^j) = 0 & g(u^j|λ^j,z*) ≤ g(x^j|λ^j,z*)
         x^j = u^j
         f(x^j) = f(u^j)
      Else If cvio(u^j) = 0 & cvio(x^j) > 0
         x^j = u^j
         f(x^j) = f(u^j)
      Else If cvio(x^j) > cvio(u^j) > 0
         x^j = u^j
         f(x^j) = f(u^j)
      End If
      Add new individual to EP if no individual in EP dominates it
      Remove all the individuals dominated by new individual from EP
   End For
End While
```

Figure 3.5 Pseudo code for MODE/D

3.4.2.2 Non-dominated Sorting Genetic Algorithm-II

NSGA-II is proposed by Deb, Pratap, Agarwal, and Meyarivan (2002) and become one of the most widely used algorithms in multi-objective optimization. Main stream, operators and parameters of NSGA-II utilized in this study are the same as NSGA-II proposed by (Deb et al., 2002). This algorithm starts with an initial population (P_1) of *NP, D*-dimensional vectors generated from a uniform distribution within the range between lower bound (*LB*) and upper bound (*UB*) for each dimension. Then, the offspring population (O_1) is obtained by using simulated binary crossover (SBX) and polynomial mutation operators proposed by (Deb & Agrawal, 1995). The algorithm form the combined population R_t by merging P_1 and O_1. Next, R_t is sorted into a number of fronts F_{it} by non-dominated sorting approach (Deb et al., 2002). In this stage, the constraint handling rules proposed by Deb (2000) are adapted to non-dominated sorting approach as follows.

- Any feasible solution is assigned to a better front than any infeasible solution.
- All feasible solutions are sorted into a number of fronts according to their objective function values.
- Among two infeasible solutions, the one having smaller constraint violation is assigned to a better front.

The individuals from the best fronts form the new population P_{t+1} with size *NP*. As size of a front may not be equal to *NP*, all the individuals in a front may not be selected for P_{t+1}. In this case, crowding distance approach (Deb et al., 2002) is used. The individuals with high crowding distance value are selected for P_{t+1}. Then, the new offspring population is formed (O_{t+1}), and the same operations continue until the stopping criterion is met. Operations of NSGA-II are summarized in Figure 3.6.

Initialize algorithm parameters $NP, CR, MR, \eta_c, \eta_m$
Generate an initial population P_1 of NP individuals from uniform distribution within the range [LB,UB]
Calculate objective function values of each individual in P_1
Sort P_1 into frontiers $F = (F_1, F_2, \ldots)$ by using non-dominated sort procedure
$EP_1 = F_1$
t=1
While Stopping criterion is not met
    $P_{t+1} = \emptyset$
    $O_t = \emptyset$
    $\mathrm{EP}_{t+1} = \emptyset$
    $\mathrm{IEP}_t = \emptyset$
    While $s(O_t) \neq NP$
        If $rand \in [0,1] \leq CR$
            Select two parent individuals p1 and p2 randomly from P_t
            Apply simulated binary crossover to generate new individuals c1 and c2
            If $rand \in [0,1] \leq MR$
                Apply polynomial mutation to c1
            End If
            If $rand \in [0,1] \leq MR$
                Apply polynomial mutation to c2
            End If
            $O_t = O_t \cup c1$
            $O_t = O_t \cup c2$
        End If
    End While
    Calculate objective function values of each individual in O_t
    $R_t = P_t \cup O_t$
    Sort R_t into frontiers $F = (F_1, F_2, \ldots)$ by using non-dominated sort procedure
    i=1
    While $s(P_{t+1} \cup F_i) \leq NP$
        $P_{t+1} = P_{t+1} \cup F_i$
        i=i+1
    End While
    Calculate crowding distance values for individuals in F_i
    Sort F_i according to crowding distance values in descending order
    $P_{t+1} = P_{t+1} \cup F_i\{1:[NP - s(P_{t+1})]\}$
    $IEP_t = EP_t \cup P_{t+1}$
    Sort IEP_t into $F = (F_1, F_2, \ldots)$ by using non-dominated sort procedure
    $EP_{t+1} = F_1$
    t=t+1
End While

Figure 3.6 Pseudo code for NSGA-II

3.5 Risk Monitoring and Control Phase

After the risk mitigation strategies are determined, outcomes of these strategies are continually monitored and reviewed. In this stage, changes in the supply chain environment and risk level are monitored and the management takes actions to ensure the continuous improvement in supply chain competitiveness. Moreover, risk identification, assessment and mitigation stages can be reiterated in case of a substantial change in supply chain environment. Furthermore, the criteria for risk assessment can be reconsidered to improve the performance of the DSS.

3.6 Conclusion

In this chapter, the proposed DSS for global SCRM is presented. The proposed DSS consists of risk identification, risk assessment, risk mitigation and risk monitoring and control phases. In risk identification phase, inbound and/or outbound risks are identified and quantified by statistical models according to user's preference. Afterwards, the critical sub-network in terms of risk is identified through a multi-criteria risk assessment procedure. In the risk mitigation phase, a multi-objective simulation-based optimization algorithm is proposed to determine the best parameter values for the risk mitigation strategies. In the simulation phase, an embedded replication number control mechanism is developed to ensure that the simulation results are obtained at required precision. In the optimization phase, MODE/D is proposed for the optimization of safety stock and supplier flexibility levels. Finally, in risk monitoring and control phase, the supply chain performance is monitored and reviewed continuously. If it is needed, risk identification, risk assessment, risk mitigation and risk monitoring and control phases can be reiterated.

Performance of the proposed DSS is evaluated in terms of efficiency and effectiveness. Total annual holding cost represents the efficiency of the SCRM, while PF ratio is used as an effectiveness measure. These performance measures conflict with each other by their nature. The aim of this thesis is to propose tradeoff solutions for SCRM in terms of efficiency and effectiveness objectives. In the subsequent chapter, the proposed DSS is implemented to a real-world automotive supply chain network spread on Europe.

CHAPTER FOUR
IMPLEMENTATION OF THE PROPOSED DECISION SUPPORT SYSTEM TO AN AUTOMOTIVE SUPPLY CHAIN

4.1 Introduction

In this chapter, the proposed DSS is implemented to a real-world automotive supply chain spread on Europe. The focal supply chain is related to a company that is a leading global supplier of electronics for automotive industry. The product of the company is harness that constitutes electrical or electronic distribution systems in automobiles. Harness is an assembly of cables and wires, and specialized to the type of automobiles. Therefore, product variety of the company is very high and consequently, the company has to maintain vast amount of component inventory.

As the customers of the company are just-in-time automobile manufacturers, backlogging is not allowed throughout the supply chain. Therefore, in case of a shortage or delay risk, components or products are transported by premium freights. As premium freights are last minute shipments transported by airlines, they incur very high costs to the company in a short time frame. Under this fact, the company aims to minimize premium freights. However, this goal can be achieved by increasing supplier flexibility, safety stock, and production levels. Consequently, annual holding cost of the supply chain increases considerably. Therefore, the company seeks compromise solutions that constitute tradeoff between holding cost and premium freight objectives.

Under this setting, the proposed DSS is implemented to the supply chain for compromise SCRM solutions that are suitable to holding cost and premium freight objectives. The implementation is conducted through risk identification, risk assessment, risk mitigation, and risk monitoring and control phases for inbound and outbound risk management cases. The results obtained by the proposed DSS are compared with the performance values related to the current operating condition of the supply chain and the results obtained by NSGA-II. Additionally, the results are discussed by a managerial perspective.

This chapter is further organized as in the following. In Section 4.2, the focal supply chain under concern is introduced. In Section 4.3, implementation of the proposed DSS in an inbound risk management case is demonstrated. In Section 4.4, implementation of the DSS in an outbound risk management case is presented. Finally, in Section 4.5, concluding remarks about the implementation of the proposed DSS are provided.

4.2 The Focal Supply Chain

The supply chain considered in this thesis consists of 752 suppliers, 12 plants and 55 customers. Components supplied from the suppliers are assembled together in the plants owned by the company to obtain harnesses. The plants have separate inventory systems and make their ordering decisions independently. The customers are just-in-time automobile manufacturers. Therefore, backlogging is not allowed in the supply chain. In case of a shortage risk, a premium freight is requested.

Premium freights are last-minute shipments transported by airlines. The premium freights requested by customers are called outbound premium freights. In similar way, the premium freights requested by plants are called inbound premium freights. Premium freight is an effective contingency strategy. However, it incurs very high costs to the responsible agent due to its setup cost and transportation mode. Additionally, it is an indicator of vulnerability of the supply chain to supply chain risks. Hence, in this study, premium freight is used to measure the performance of the risk mitigation strategies in addition to the cost measures.

The supply chain under concern operates six days in a week and 48 weeks in a year. Customers share their demand forecast with the plants in weekly basis. The plants adjust the customer demand forecasts by a demand forecast adjustment factor. The plants use the adjusted demand forecasts in developing their production plan and determining the order sizes to be placed to their suppliers. The plants use a periodic order-up-to policy, and they place their orders at the beginning of each week. Shipments and deliveries are made only in working days. The plants determine their order quantities by considering safety their stock level, transportation lead time and average daily consumption of material as well as quantity flexibility limits of the suppliers. The suppliers transmit orders at the same day with the order placed. Production and storage processes of the suppliers are not considered in this thesis.

All the necessary information about the materials (i.e. unit prices, transportation lead times, and average daily consumption) is obtained from the plan for every part spreadsheets used by the plants. Currently, the plants use the demand forecast adjustment factor of 1.067. The plants have safety stock level of 3.5 days for each material. Supplier flexibility is determined as a percentage in quantity flexibility contracts. $Fl\%$ flexibility means that plants cannot increase or decrease its order quantity by $Fl\%$ from the contracted quantity. Currently, quantity flexibility limit of each supplier is 50%. In case of a request of a higher flexibility limit from the contracted limit, the supplier increases the unit price of the material to leverage its additional costs incurred due to the increase in flexibility. By taking the advantage of the supply chain manager's experience, the relationship between supplier flexibility and unit price is modeled by the following equation.

$$unit\ price^{new} = \left[\frac{100 + 0.2(Fl^{new} - Fl^{curr})}{100}\right] unit\ price^{curr} \tag{4.1}$$

where $unit\ price^{curr}$ is the current unit price under current flexibility limit Fl^{curr}, and $unit\ price^{new}$ is the new unit price under new flexibility limit Fl^{new}.

In subsequent sections, identification and modeling of the critical sub-networks through inbound and outbound risk management considerations are presented.

4.3 Inbound Risk Management

In this section, inbound risks of the supply chain are focused on. Hence, the materials are investigated in terms of their criticality by the proposed risk assessment procedure. As the inbound supply chain inventory consists of 7300 materials consumed by 12 plants, it is unreasonable to assess the risks related to all materials. Therefore, the materials that have a considerable share on annual inbound premium freight costs are identified by using Pareto principle. As a result, 37 out of 7300 materials presenting 80% of annual inbound premium cost are selected for the risk assessment.

4.3.1 Risk Identification Phase

Firstly, supply chain risks related to the focal supply chain network are identified. The inbound risks related to the focal supply chain are identified as supplier delivery delay and delivery quantity loss. The inbound risks are modeled by their occurrence and severity values. The fractions of late and undershipped deliveries are obtained by past order data and used as the occurrence values of delivery delay and delivery quantity loss, respectively. To quantify the severity values of inbound risks, delivery lateness and quantity loss data obtained from past order records are fitted to a number of probability distributions.

The outbound risk is identified as variability in the material consumption. However, as a material type can be used in production of hundreds of different product types, it is impractical to model material consumption variability based on customer demand variability. Therefore, material consumption variability is assumed to follow a uniform distribution varying between 50% and 150% of average daily consumption in parallel with the supply chain manager's opinion.

4.3.2 Risk Assessment Phase

In this phase, the focal supply chain is decomposed into a critical sub-network by considering inbound supply chain risk performance. The criteria for risk assessment are identified by the supply chain manager as “the number of inbound premium freights in previous year”, “monetary value of inbound premium freights in previous year” and “average weekly consumption of materials”. However, these criteria are assessed by a number of plants with different ratings. Therefore, multiple decision matrices are formed. As stated previously, these decision matrices should be merged into unique decision matrix by using a group decision making approach. In this study, the decision matrices are merged by averaging the ratings of the plants.

The overall criticality indices calculated by using TOPSIS are presented in Table 4.1. As reported in the table, the most critical material is M1. The critical sub-network related to M1 is illustrated in Figure 4.1.

Table 4.1 Overall criticality indices for the materials

Material	CC_i	Material	CC_i	Material	CC_i	Material	CC_i
M1	0.14	M9	0.03	M8	0.02	M21	0.01
M5	0.11	M24	0.03	M36	0.02	M31	0.01
M16	0.08	M34	0.03	M18	0.02	M12	0.01
M2	0.05	M6	0.03	M32	0.02	M28	0.01
M3	0.05	M29	0.03	M33	0.02	M20	0.01
M14	0.05	M17	0.02	M30	0.02	M26	0.00
M11	0.04	M19	0.02	M10	0.01	M35	0.00
M7	0.04	M22	0.02	M27	0.01		
M13	0.04	M4	0.02	M23	0.01		
M25	0.03	M15	0.02	M37	0.01		

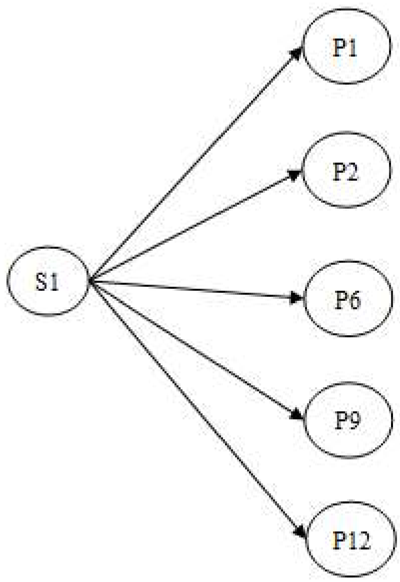

Figure 4.1 The critical sub-network identified in case of inbound risk management

4.3.3 Risk Mitigation Phase

In this phase, the proposed simulation-based optimization framework is implemented to the critical sub-network to determine the best supplier flexibility and safety stock levels. In this context, a simulation model of the critical sub-network is developed. In the simulation model, daily operations of supply chain agents such as updating inventory position, placing order and requesting premium freight are defined realistically. The simulation model is integrated to MODE/D to determine the supplier flexibility and safety stock levels that yield the best holding cost and inbound PF ratio values. In subsequent sections, the simulation model developed for the critical sub-network, the computational experiments and the numerical results are presented in detail.

4.3.3.1 Simulation Model of the Critical Sub-Network

In this section, the simulation model developed for the critical sub-network is explained. As stated previously, the plants under concern use periodic order-up-to policy to maintain their material inventory. However, order quantities are bounded by supplier flexibility limits that are contracted as the same levels for all plants. In addition, plants are subjected to stock-out risks arisen from supply-side and demand-side uncertainties. However, the supply chain is a just-in-time system in which stock-outs are not allowed. Therefore, plants have to request a premium freight from their supplier in case of a stock-out risk. Daily operations of the plants are described in the following.

At the beginning of each day t, the plants check their inventory position (see Eq. 4.2).

$$IP_p(t) = IP_p(t-1) + D_p(t) - C_p(t-1) \tag{4.2}$$

where $IP_p(t)$ is the inventory position of plant p on day t, $D_p(t)$ is the delivery amount on day t, and $C_p(t-1)$ is the amount of material consumed by plant p on day $t-1$.

At the beginning of each week, plants calculate their material requirement for the next week (see Eq. 4.3).

$$RQ_p(t) = max\{0, \left[AC_p\left(SS_p + WD_p + TLT_p\right) - IP_p(t)\right]\} \tag{4.3}$$

where $RQ_p(t)$ is the required amount of material, AC_p is the average daily consumption of the material, WD_p is number of working days in a week, and TLT_p is the average transportation lead time.

As stated previously, order quantities are bounded by supplier flexibility limits. Therefore, the plants have to place orders ($OQ_p(t)$) within the flexibility limits (see Eq. 4.4).

$$AC_pWD_p(100 - Fl)/100 \leq OQ_p(t) \leq AC_pWD_p(100 + Fl)/100 \tag{4.4}$$

Moreover, if inventory position of a plant falls below the safety stock level on any day t except the regular ordering days (at the beginning of each week), a premium freight is requested from supplier. Premium freights ($IPF_p(t)$) are independent from quantity flexibility limits, and calculated as in the following.

$$IPF_p(t) = AC_p\left[WD_p - (t_c - t_o) + TLT_p\right] \tag{4.5}$$

where t_c and t_o are current time and nearest time of a regular order placed, respectively.

The performance measures considered are "annual holding cost" and "inbound PF ratio". Annual holding cost of supply chain is the sum of annual holding costs of the plants related to the critical material. Inbound PF ratio is the ratio of total amount of premium freights requested by the plants to total amount of orders placed by the plants related to the critical material. These measures are utilized as objective functions of MODE/D which constitutes the optimization phase of the proposed simulation-based optimization framework.

4.3.3.2 Computational Experiments

In this section, supplier flexibility and safety stock levels yielding the best holding cost and inbound PF ratio of the automotive supply chain under concern are determined by using the proposed simulation-based optimization algorithm. Performance of the proposed algorithm is evaluated in comparison with the performances of NSGA-II and current operating condition of the supply chain. Computational experiments related to the implementation of the proposed framework are conducted by MATLAB.

In the simulation phase, replication length and warm-up period are determined as two years and two weeks, respectively. e_{max}, minimum and maximum replication numbers are specified as 15%, 3 and 10, respectively. As stated previously, the daily material consumption can vary because of the demand variability. In parallel with the supply chain manager's opinion, daily material consumption of each plant is modeled by a uniform distribution with parameters $\left[0.5AC_p, 1.5AC_p\right]$. In addition, delivery performance of the supplier is variable. To model the delivery performance of the supplier, delivery loss and delay data are obtained from past order records of the plants and are fitted to a number of probability distributions. Delivery loss is the ratio of lost delivery quantity to order quantity. Delivery delay is the delay of delivery in days. The occurrence probability of a delivery loss is obtained as 0.05. The delivery loss quantity is best fitted to lognormal distribution with parameters 0.52 and 0.23. Additionally, the occurrence probability of a delivery delay is 0.06, and the delivery delay time is best fitted to lognormal distribution with parameters 1.43 and 0.46.

In the optimization phase, the parameters of MODE/D (H, T, CR, F) and NSGA-II $(NP, CR, MR, \eta_c, \eta_m)$ are tuned by experimental design. Particularly, the parameter δ for MODE/D is specified as 0.9. By considering the common practice of the focal supply chain, feasible ranges for the safety stock and supplier flexibility levels are determined as [1, 10] and [0, 1], respectively. Nadir and reference points (z^{nad} and z^*) are determined by running the proposed algorithm for a very long time in single objective setting in terms of each objective. The worst objective values are determined as nadir point, $z^{nad} = [11633.26,\ 0.26]^T$. In addition, the best objective values are determined as reference point, $z^* = [3467.62,\ 0.01]^T$. The utopian point is specified as falling below the reference point, $z^{**} = [3000, 0]^T$. The stopping criterion of both algorithms is settled on 100 generations without an improvement on any objectives.

To measure the performance of the algorithms, hypervolume indicator is used in this thesis. This indicator corresponds to the hypervolume of the portion of objective space that dominated by the Pareto frontier. To calculate hypervolume indicator, the objective space should be bounded by a bounding reference point dominated by all Pareto frontier points (Knowles, Thiele, & Zitzler, 2006). In this study, nadir point (z^{nad}) is used as bounding reference point.

In the subsequent sections, validation and verification of the simulation model is presented. Afterwards, the experimental design approach utilized to determine the parameters of the algorithm yielding the best algorithm performance is explained. Finally, the results obtained from MODE/D are presented in comparison with current operating condition of the supply chain and the results obtained from NSGA-II.

4.3.3.2.1 Verification and Validation of the Simulation Model. First of all, accuracy of the simulation results is verified. In this context, the MATLAB program related to the simulation model of the critical sub-network is debugged and internal logic of the program is investigated carefully. After verification of the simulation model, a set of preliminary simulation experiments are conducted to investigate the behavior of the model. Purposely, simulation experiments are conducted under various setting of supplier flexibility and safety stock levels, and the model behavior is compared to the real system behavior under different settings. In this stage, we broadly benefit from the comments of supply the chain manager of the company. As a result of the validation experiments, the simulation model is confirmed to be valid as it reflects the characteristics of the real system.

4.3.3.2.2 Experimental Design. To determine the parameter values yielding the best performance for MODE/D and NSGA-II, Taguchi method (Roy, 2001) is utilized. Taguchi classifies the factors affecting the response into signal and noise factors, and proposes a robust design approach to reduce the noise factors. In this context, signal to noise (S/N) ratios are utilized as the measure of robustness. Purposely, larger S/N ratios correspond to better performance.

For both MODE/D and NSGA-II, three levels of algorithm parameters (see Tables 4.2 and 4.3) are considered, and L27 orthogonal array is used. The main effects of S/N ratios on MODE/D and NSGA-II parameter levels are illustrated in Figures 4.2 and 4.3. As one can infer from the figures, the best parameter levels for MODE/D are $H = 29$, $T = 0.7 \times NP$, $CR = 0.75$, and $F = 0.50$. In addition, the best parameter levels for NSGA-II are $NP = 10$, $\eta_c = 25$, η_m=5, $CR = 0.25$, and $MR = 0.75$.

Table 4.2 Parameter levels for MODE/D

Level	H	T	CR	F
1	9	$0.3 \times NP$	0.25	0.25
2	19	$0.5 \times NP$	0.50	0.50
3	29	$0.7 \times NP$	0.75	0.75

Table 4.3 Parameter levels for NSGA-II

Level	NP	η_c	η_m	CR	MR
1	10	5	5	0.25	0.25
2	20	15	15	0.50	0.50
3	30	25	25	0.75	0.75

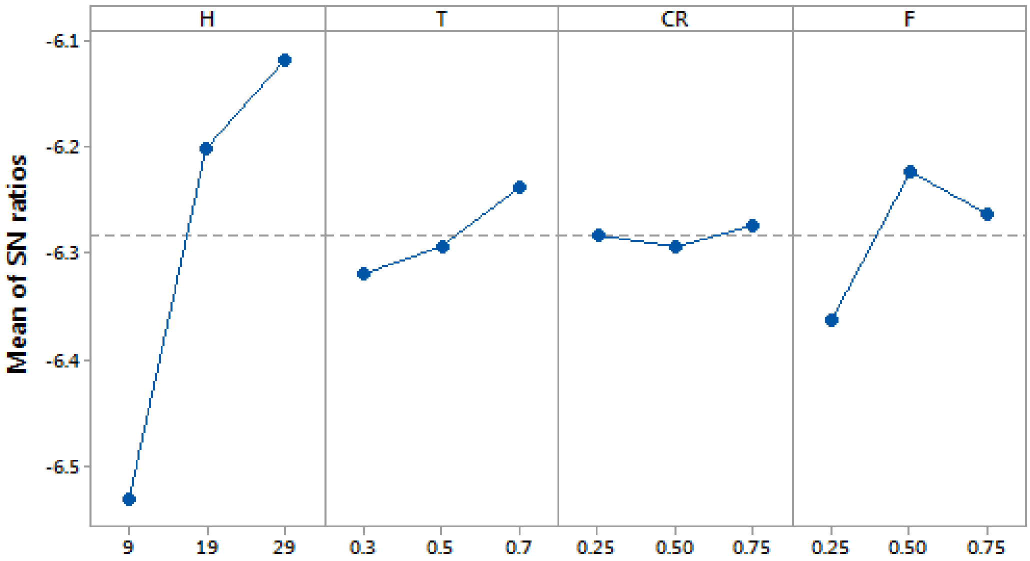

Figure 4.2 Main effects of S/N ratios for MODE/D parameters

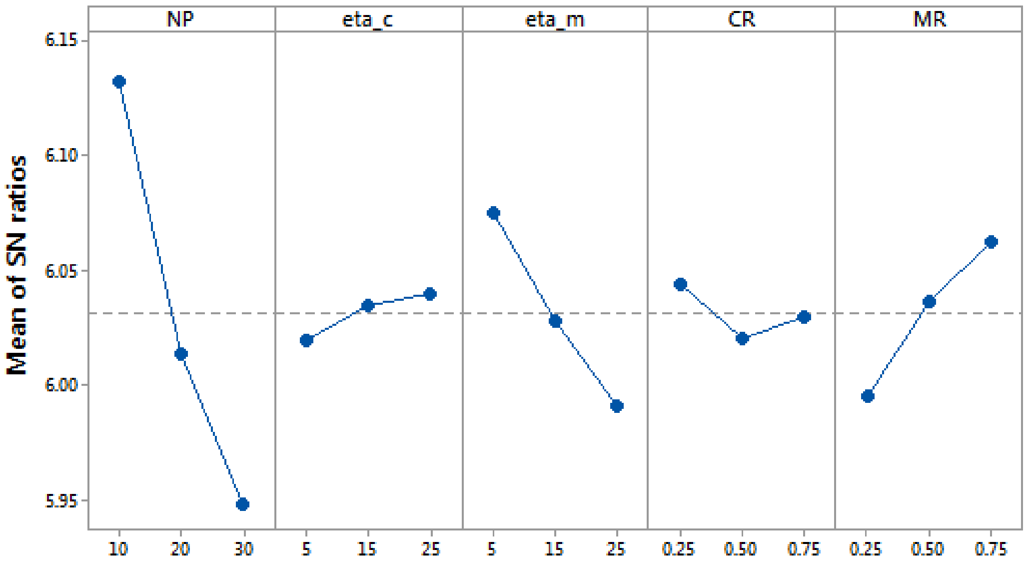

Figure 4.3 Main effects of S/N ratios for NSGA-II parameters

4.3.3.2.3 Numerical Results. In this section, the results obtained by the proposed framework consisting of MODE/D algorithm with tuned parameters are presented. Additionally, the results are compared with the results obtained by using NSGA-II and those of the current operating condition of the supply chain.

Both of the algorithms are run for 15 times, and the results are summarized in Table 4.4. As reported in Table 4.4, MODE/D yields better results than NSGA-II.

Table 4.4 Comparison of hypervolume values of the algorithms

	Average	Best	Std. Dev.
MODE/D	0.4941	0.5001	0.0031
NSGA-II	0.4853	0.4880	0.0020

In Figure 4.4, Pareto frontiers obtained by using MODE/D and NSGA-II are illustrated. Additionally, performance values obtained by simulating the current operating condition of the supply chain (safety stock for 3.5 days, 50% supplier flexibility) are demonstrated in Figure 4.4. As one can infer from the figure, both algorithms yield better results than the current operating condition of the supply chain. The results also reveal that, MODE/D offers better performance than NSGA-II.

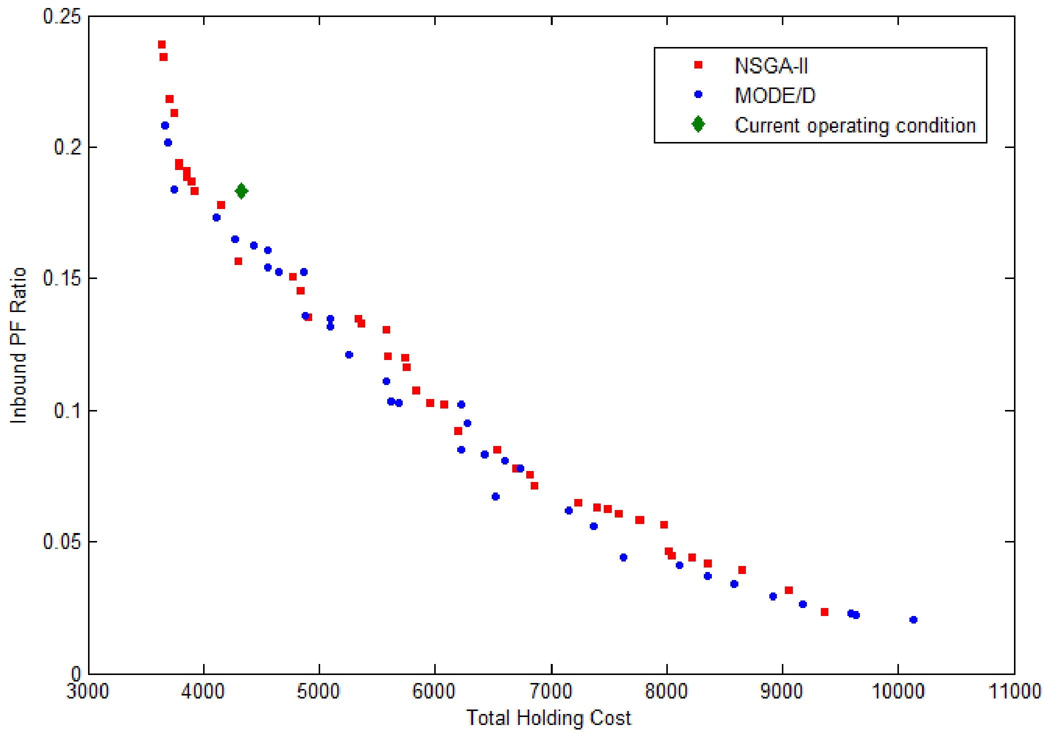

Figure 4.4 Pareto frontiers obtained by MODE/D and NSGA-II in case of inbound risk management

Managers of the supply chain may choose any point from the Pareto frontiers presented in Figure 4.4 by considering the supply chain competition strategy. By comparing the total holding cost and inbound PF ratio performances of the alternative solutions, the managers can consider a broad decision spectrum and consequently take the advantage of more flexible decision making. An example comparison of current operating condition and alternative solutions obtained by the proposed framework is presented in Table 4.5. As reported in Table 4.5, total holding cost of the supply chain can be reduced from €4326 to €3745 at the same inbound PF ratio performance (see Pareto-Optimal Solution 1). In addition, inbound PF ratio can be decreased to 0.17, at a lower holding cost than the current holding cost (see Pareto-Optimal Solution 2). Furthermore, managers may prefer to reduce inbound PF ratio more considerably. In this case, total holding cost will increase due to the increase in both supplier flexibility and safety stock levels (see Pareto-Optimal Solution 3).

Table 4.5 Comparison of current operating condition with the Pareto-optimal solutions in case of inbound risk management

Parameters and Performance metrics	Current Operating Condition	Pareto-Optimal Solution 1	Pareto-Optimal Solution 2	Pareto-Optimal Solution 3
F	50%	12%	46%	73%
SS_1	3.50	5.81	4.03	6.34
SS_2	3.50	7.70	9.86	3.72
SS_3	3.50	3.95	9.49	4.88
SS_4	3.50	5.17	5.81	4.55
SS_5	3.50	6.33	8.47	3.19
Total Holding Cost	€4326	€3745	€4273	€4883
Inbound PF Ratio	0.18	0.18	0.17	0.14

4.3.4 Risk Monitoring and Control Phase

Once the supplier flexibility and safety stock levels are determined, the cost and premium freight performance of the supply chain is monitored and reviewed continuously. In case of a major change in supply chain performance or in supply chain strategy, another alternative solution suitable to the new situation from Pareto optimal solutions may be adopted. Furthermore, if it is needed, risk identification, assessment and mitigation stages can be reiterated.

4.4 Outbound Risk Management

In this section, we focus on outbound risks of the supply chain. Consequently, the products are investigated in terms of their criticality by the proposed risk assessment procedure. Since there exist 2700 different types of products produced by the plants, it is unreasonable to assess the risks related to all products. Hence, the products that have a considerable share on annual outbound premium freight costs are identified by using Pareto principle. As a result, 27 out of 2700 products presenting 80% of annual outbound premium freight cost are selected for risk assessment.

4.4.1 Risk Identification Phase

As outbound risk management considers supply chain risks related to finished products, demand-side risks become an issue in addition to the supply-side risks. Hence, both inbound and outbound risks are taken into account in outbound risk management case. The inbound risks are identified as supplier delivery delay and delivery loss. As in inbound risk management case, the inbound risks are modeled by their occurrence and severity values. The occurrence and severity values are quantified by the probability distributions derived from past order data as in Section 4.3.1.

Outbound risks are identified as customer demand variability and deviation of actual customer demand from shared demand information. These risks are modeled as ordinary variabilities that occur every week and only severity values of them are modeled. To model outbound risks, actual demand and demand deviation data obtained from the past customer demand records are fitted to a number of probability distributions.

4.4.2 Risk Assessment Phase

In this phase, the focal supply chain is decomposed into a critical sub-network by considering outbound supply chain risk performance. The criteria for risk assessment are identified by the supply chain manager as "the number of outbound premium freights in previous year", "monetary value of the outbound premium freights in previous year" and "annual sales of the products". The overall criticality indices calculated by using TOPSIS method are presented in Table 4.6. As can be inferred from the table, the most critical product is PR1. The critical sub-network related to PR1 is presented in Figure 4.5.

Table 4.6 Overall criticality indices for the products

Products	CC_i
PR1	0.18
PR11	0.14
PR6	0.14
PR2	0.12
PR3	0.10
PR5	0.10
PR4	0.08
PR12	0.07
PR7	0.05
PR13	0.05
PR8	0.04
PR10	0.03
PR9	0.03

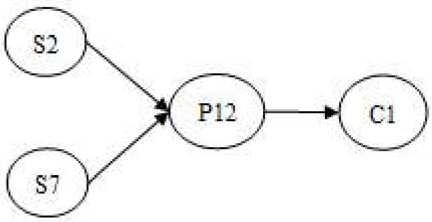

Figure 4.5 The critical sub-network identified in outbound risk management case

4.4.3 Risk Mitigation Phase

In this phase, the proposed simulation-based optimization framework is implemented to the critical sub-network to determine the best supplier flexibility and safety stock levels. In this context, simulation model of the critical sub-network is developed. In the simulation model, daily operations of the supply chain such as receiving demand information, production planning, placing orders and requesting premium freights are defined realistically. The simulation model is integrated to MODE/D to determine the parameter values that yield the best holding cost, inbound PF ratio, and outbound PF ratio. In subsequent sections, the simulation model developed for the critical sub-network, the computational experiments, and the numerical results are presented in detail.

4.4.3.1 Simulation Model of the Critical Sub-Network

In this section, the simulation model developed for the critical sub-network is explained. The customer weekly shares its demand forecast for succeeding week with the manufacturer. The plant uses the demand forecast in determining the order sizes to be placed to corresponding suppliers and updating the production plan. As stated previously, the plant utilizes periodic order-up-to policy to maintain its material inventory. At the beginning of each week, it calculates weekly requirements for each material and places orders to suppliers within suppliers' flexibility limits to meet its weekly requirements. However, there is a stock-out risk due to inbound and outbound risks. In case of a stock-out risk, the plant has to request a premium freight from its supplier. This type of premium freight is called as inbound premium freight. Similarly, in case of a delay risk in the final product delivery to the customer, the plant has to ship the final products by a premium freight. This type of premium freight is called as outbound premium freight. Daily operations of the plant are described in the following.

At the beginning of each day *t*, inventory positions of each material *i* ($IP_i(t)$) and final product ($IP_{FG}(t)$) are calculated by the following equations.

$$IP_i(t) = IP_i(t-1) + D_i(t) - C_i(t-1) \tag{4.6}$$

$$IP_{FG}(t) = IP_{FG}(t-1) + FG(t-1) - CD(t) - OPF(t) \tag{4.7}$$

where $D_i(t)$ is the delivery amount of material *i* on day *t*, $C_i(t-1)$ is the amount of material consumed on day $t-1$, $FG(t-1)$ is the number of final product produced on day $t-1$, $CD(t)$ is the customer demand on day *t*, and $OPF(t)$ is the outbound premium freight for final product shipped to the customer on day *t*.

At the beginning of each week, customer demand forecast ($CDF(t)$) information is received, and it is adjusted by demand forecast adjustment factor (γ) to obtain the plant demand forecast ($PDF(t)$).

$$PDF(t) = \gamma CDF(t) \tag{4.8}$$

$PDF(t)$ is used to develop the daily production plan of the corresponding week. At the beginning of each week, production plan of each day *t* ($PP(t)$) is determined as in the following.

$$PP(t) = [PDF(t) - IP_{FG}(t)]/[WD - PLT] \tag{4.9}$$

where WD is the number of working days in a week, and PLT is the production lead time for the final product.

Afterwards, weekly requirements for each material *i* ($R_i(t)$) are calculated by considering bill of materials, safety stock levels, inventory positions and transportation lead times of the materials.

$$R_i(t) = \left[1 + \frac{SS_i + TLT_i}{WD - PLT}\right] b_i PDF(t) - IP_i(t) \tag{4.10}$$

where b_i is number of material *i* needed to produce the final product, SS_i is the safety stock level of material *i* in days, and TLT_i is the transportation lead time for material *i*. The bill of material related to the product under concern (PR1) is reported in Table 4.7.

Table 4.7 Bill of material for the critical product

Material	Supplier	Quantity
M2	S2	1
M22	S2	3
M71	S7	3
M73	S7	3
M76	S7	1
M79	S7	3

As stated previously, order quantities are bounded with quantity flexibility contracts made between the plant and its suppliers. Therefore, the order quantity ($OQ_i(t)$) is calculated as follows:

$$AC_i WD(100 - Fl_i)/100 \leq OQ_i(t) \leq AC_i WD(100 + Fl_i)/100 \tag{4.11}$$

where AC_i and Fl_i are the average daily consumption and quantity flexibility limit of material i, respectively.

In addition, if inventory position of any material falls below the safety stock level on any day t except the regular ordering days, an inbound premium freight is requested from corresponding supplier. Herein, amount of the inbound premium freight ($IPF_i(t)$) is calculated as in the following.

$$PF_i(t) = \left[\sum_{j=t}^{t_o+WD-1} b_i PP(j) \right] + AC_i TLT_i \tag{4.12}$$

where t_o is the nearest time of a regular order placed.

At the end of each day, $FG(t)$ is recorded. $FG(t)$ may be less than $PP(t)$ in case of a material shortage. In this case, the amount that is not produced in $PP(t)$ is added to $PP(t+1)$.

At the end of each week, customer demand is realized. As stated previously, customer demand cannot be backordered. If there is a risk of customer delivery delay, the risky portion of final products demanded by the customer is shipped to the customer by an outbound premium freight ($OPF(t)$).

The performance measures considered are "annual holding cost", "inbound PF ratio" and "outbound PF ratio". Annual holding cost of supply chain is the sum of annual holding costs of the critical product and materials related to the critical product. Inbound PF ratio is the proportion of inbound premium freights requested by the plant to total orders placed by the plant. Similarly, outbound PF ratio is the proportion of outbound premium freights shipped to customer to total customer demand. These measures are utilized as objective functions of MODE/D which constitutes the optimization phase of the proposed framework.

4.4.3.2 Computational Experiments

In this section, demand forecast adjustment factor (γ), supplier flexibility and safety stock levels yielding best holding cost, inbound PF ratio, and outbound of the automotive supply chain under concern are determined by using the proposed simulation-based optimization algorithm. The performance of the proposed algorithm is evaluated in comparison with the performances of NSGA-II and current operating condition of the supply chain. Computational experiments related to the implementation of the proposed framework are conducted in MATLAB.

In the simulation phase, replication length and warm-up period are determined as two years and two weeks, respectively. e_{max}, minimum and maximum replication numbers are specified as 15%, 3 and 10, respectively. As stated previously, the customer shares its demand forecast on weekly basis and manufacturer adjusts the customer demand forecast by demand forecast adjustment factor (γ) to develop its weekly production plan. Currently, the manufacturer uses 1.067 as the demand forecast adjustment factor value. To develop a customer demand model, customer demand forecast and actual customer demand data are obtained from the past demand records. The customer demand is modeled by customer demand forecast and the ratio of actual customer demand to associated customer demand forecast. Both data are fitted to a number of probability distributions while they best fit to lognormal distribution. The resulting customer demand model is presented in Table 4.8.

Table 4.8 The customer demand model

	Distribution	Mean	Std. Dev.
Demand forecast	Lognormal	6.27	0.51
Ratio	Lognormal	0.07	0.21

In order to model the supply risks, delivery loss data and delivery delay data of each supplier are obtained from past order records of the manufacturer and are fitted to a number of probability distributions. Delivery loss is considered as a ratio of lost delivery quantity to order quantity. Delivery delay is the delay of delivery arrival in days. Probabilities of these undesirable delivery situations are obtained by past order data and are reported in Table 4.9. Additionally, the probability distributions and associated parameters of delivery loss and delivery delay risks are presented in Table 4.9.

In the optimization phase, the parameters of MODE/D (H, T, CR, F) and NSGA-II ($NP, CR, MR, \eta_c, \eta_m$) are tuned by experimental design. Particularly, the parameter δ of MODE/D is specified as 0.9. By considering the common practice of the focal supply chain, feasible ranges for the demand forecast adjustment factor, safety stock and supplier flexibility levels are determined as [1, 10], [1, 10] and [0, 1], respectively. Nadir, reference, and utopian points are specified as $z^{nad} = [181062.4684,\ 0.0020, 0.3965]^T$, $z^{*} = [12296.7420, 0.0001, 0]^T$, and $z^{**} =$

$[10000, 0, 0]^T$, respectively. The stopping criterion of both algorithms is settled on 100 generations without an improvement on any objectives. To measure the performance of the algorithms, hypervolume indicator is utilized.

Table 4.9 The supplier risk model

	Delivery Loss				Delivery Delay			
Suppliers	Probability	Distribution	Mean	Std. Dev.	Probability	Distribution	Shape	Scale
S2	0.03	Normal	0.51	0.25	0.07	Weibull	1.20	2.30
S7	0.05	Normal	0.45	0.17	0.09	Weibull	1.66	1.61

In the subsequent sections, validation and verification of the simulation model is presented. Afterwards, the experimental design approach utilized to determine the values of the algorithm parameters yielding best algorithm performance is explained. Finally, the results obtained from MODE/D are presented in comparison with the results obtained from NSGA-II and current operating condition of the supply chain.

4.4.3.2.1 Verification and Validation of the Simulation Model. Firstly, the simulation model is verified by investigating and debugging the MATLAB program related to the simulation model. Afterwards, several simulation experiments are conducted by using different demand forecast adjustment factor, supplier flexibility and safety stock levels. The effects of input parameters are examined through supply chain performance measures, and then, reviewed by the supply chain manager of the company. As a result, the simulation model is confirmed to be valid, since it reflects the characteristics of the real supply chain system.

4.4.3.2.2 Experimental Design. As in Section 4.3.3.2.2, Taguchi method is utilized to determine the parameter levels yielding the best performance for MODE/D and NSGA-II. For both MODE/D and NSGA-II, three levels of algorithm parameters (see Tables 4.10 and 4.11) are considered, and L27 orthogonal array is used. The main effects of S/N ratios on MODE/D and NSGA-II parameter levels are presented in Figures 4.6 and 4.7. As one can infer from the figures, the best parameter levels for MODE/D are $H = 10$, $T = 0.5 \times NP$, $CR = 0.25$, and $F = 0.25$. In addition, the best parameter levels for NSGA-II are $NP = 80$, $\eta_c = 15$, $\eta_m = 15$, $CR = 0.50$, and $MR = 0.25$.

Table 4.10 Parameter levels for MODE/D

Level	H	T	CR	F
1	9	$0.3 \times NP$	0.25	0.25
2	10	$0.5 \times NP$	0.50	0.50
3	11	$0.7 \times NP$	0.75	0.75

Table 4.11 Parameter levels for NSGA-II

Level	NP	η_c	η_m	CR	MR
1	50	5	5	0.25	0.25
2	65	15	15	0.50	0.50
3	80	25	25	0.75	0.75

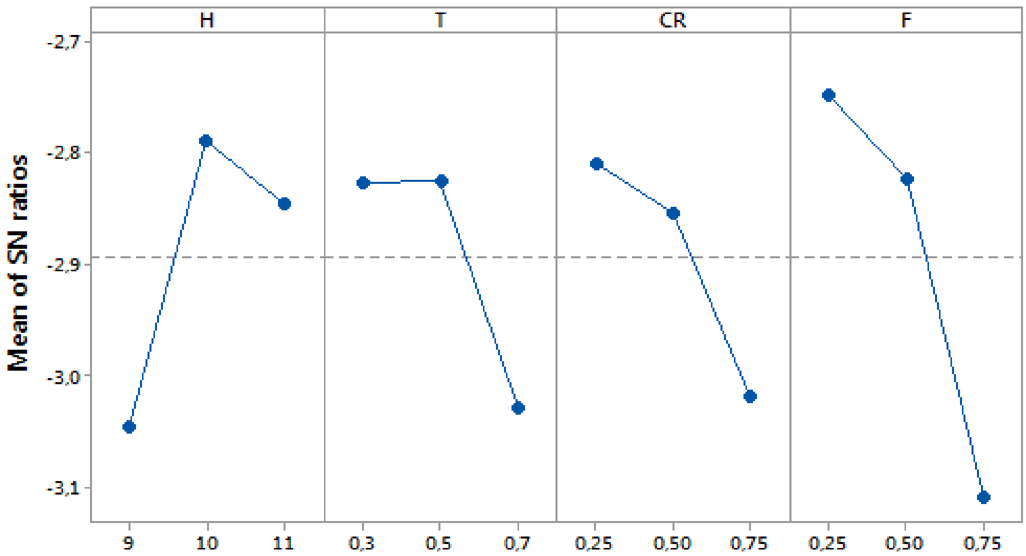

Figure 4.6 Main effects of S/N ratios for MODE/D parameters

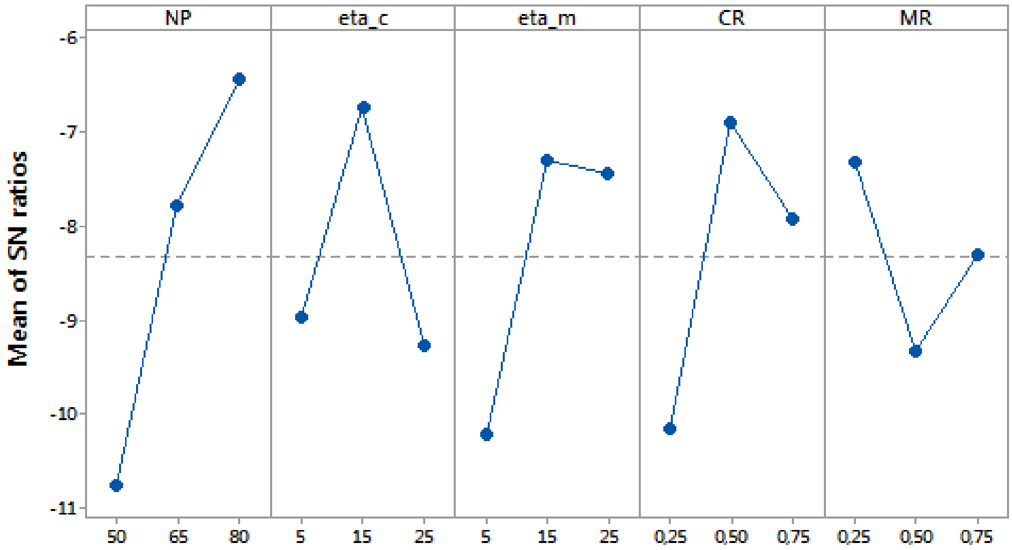

Figure 4.7 Main effects of S/N ratios for NSGA-II parameters

4.4.3.2.3 Numerical Results. In this section, the results obtained by the proposed framework consisting of MODE/D algorithm with tuned parameters are presented. Additionally, the results are compared with the results obtained by using NSGA-II and those of the current operating condition of the supply chain.

Both of the algorithms are run for 15 times, and the results are summarized in Table 4.12. As one can infer from Table 4.12, MODE/D yields better results than NSGA-II.

Table 4.12 Comparison of hypervolume values of the algorithms

	Average	Best	Std. Dev.
MODE/D	0.7355	0.7474	0.0067
NSGA-II	0.5027	0.6794	0.1423

In Figures 4.8-4.10, Pareto frontiers obtained by using MODE/D and NSGA-II are illustrated in comparison with the current operating condition of the supply chain (1.067 for demand forecast adjustment factor, 3.5 days for safety stock, 50% for supplier flexibility). As one can infer from the figure, both algorithms yield better results than the current operating condition of the supply chain. The results also reveal that MODE/D offers better performance than NSGA-II.

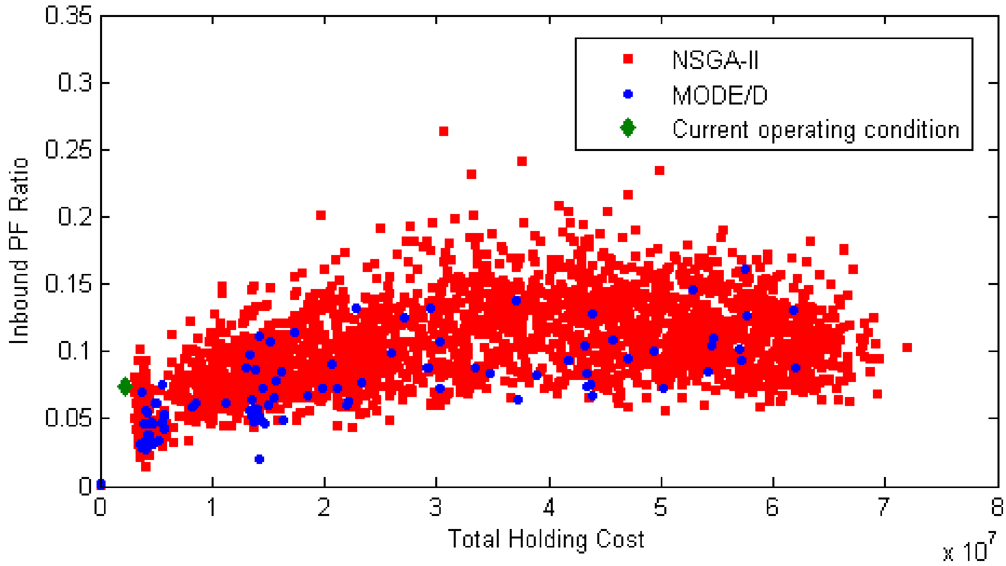

Figure 4.8 Pareto frontiers obtained by MODE/D and NSGA-II on total holding cost and inbound PF ratio dimensions

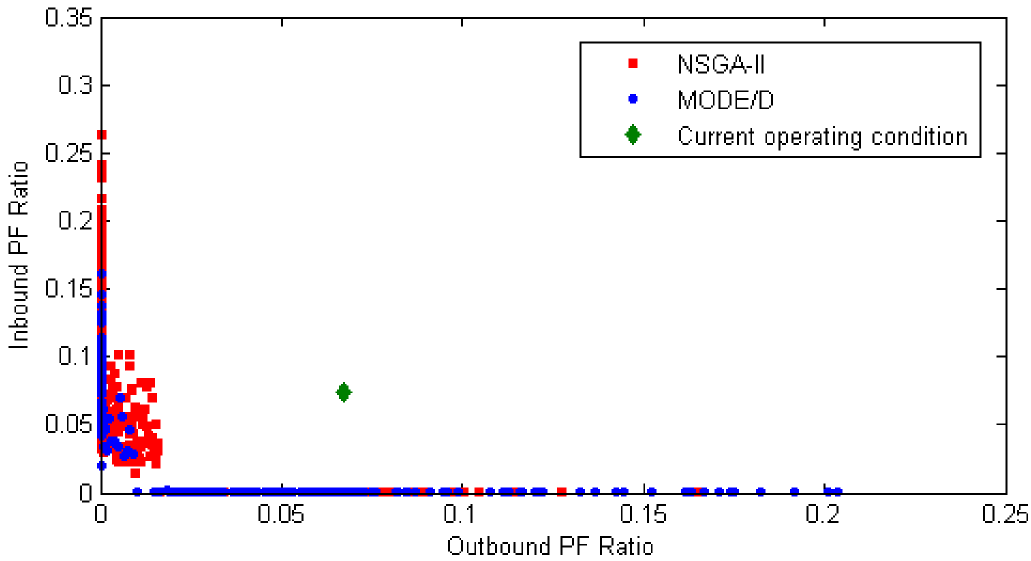

Figure 4.9 Pareto frontiers obtained by MODE/D and NSGA-II on outbound PF ratio and inbound PF ratio dimensions

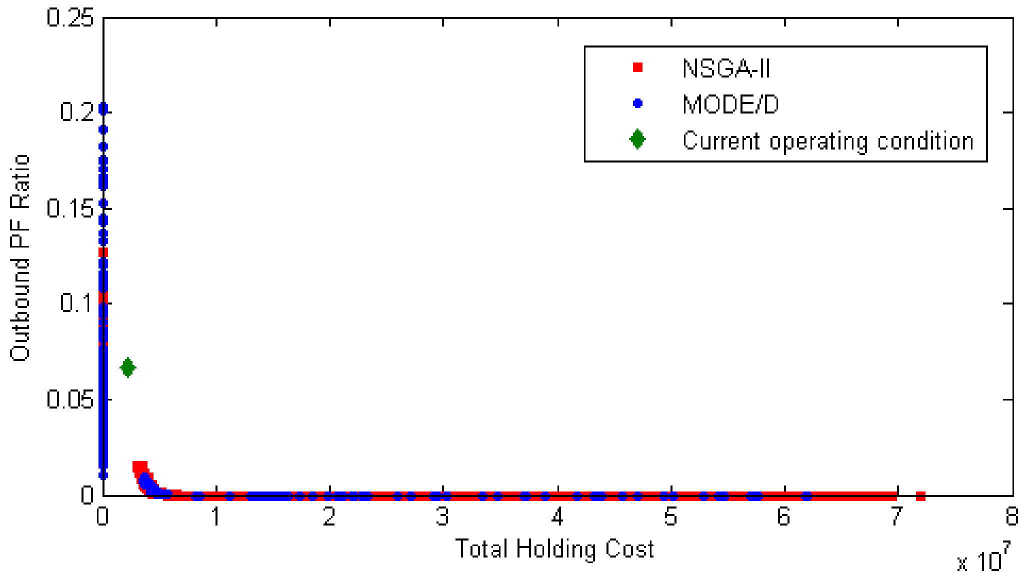

Figure 4.10 Pareto frontiers obtained by MODE/D and NSGA-II on total holding cost and outbound PF ratio dimensions

An example comparison of current operating condition and Pareto-optimal solutions is presented in Table 4.13. As one can infer from the Table, at the same outbound PF ratio performance, total holding cost and inbound PF ratio of the supply chain can be reduced to €124,389 and 0.0002, respectively (see Pareto-Optimal Solution 1). Besides, there exists an alternative solution yielding much better performance than the current supply chain performance in terms of all objectives (see Pareto-Optimal Solution 2). However, if the outbound PF ratio reduced to zero, total holding cost surges (see Pareto-Optimal Solution 3).

4.4.4 Risk Monitoring and Control

After the demand forecast adjustment factor, supplier flexibility and safety stock levels are determined in risk mitigation stage, the supply chain performance is continually monitored in terms of cost and premium freight performance. The performance of the supply chain is investigated through the supply chain management strategy and changes in supply chain environment. In case of a major change in supply chain environment or strategy, a more suitable alternative solution among Pareto optimal solutions can be applied. Alternatively, the proposed DSS can be re-implemented with new risk assessment criteria in an ultimate case.

Table 4.13 Comparison of current operating condition with the Pareto-optimal solutions in case of outbound risk management

Parameters and Performance	Current Operating Condition	Pareto-Optimal Solution 1	Pareto-Optimal Solution 2	Pareto-Optimal Solution 2
γ	1.0667	1.0004	1.0007	1.8972
SS_1	3.5000	9.6703	3.8404	7.8105
SS_2	3.5000	1.0838	5.3238	1.4295
SS_3	3.5000	3.1112	3.1045	6.1639
SS_4	3.5000	9.4767	5.3801	6.5317
SS_5	3.5000	5.7549	1.5530	4.0792
SS_6	3.5000	9.9352	7.5668	2.9718
F_1	50%	31%	35%	31%
F_2	50%	45%	37%	93%
F_3	50%	20%	56%	40%
F_4	50%	93%	79%	88%
F_5	50%	24%	47%	25%
F_6	50%	84%	8%	90%
Total Holding Cost	€2,196,235	€124,389	€57,121	€5,782,230
Inbound PF Ratio	0.0746	0.0002	0.0003	0.0524
Outbound PF Ratio	0.0672	0.0601	0.0002	0.0000

4.5 Conclusion

In this chapter, the proposed DSS for SCRM is implemented to a real-world supply chain spread on Europe. The supply chain consists of several suppliers, plants and customers. As the customers are just-in-time automobile manufacturers, backlogging is not allowed throughout the supply chain. In case of a shortage or delay risk, a premium freight is requested. Premium freights are last minute deliveries transported by airlines. Due to their transportation mode, premium freights incur very high costs to the company in a short time-frame. Therefore, the company aims at premium freight reduction along with cost reduction.

The proposed DSS is applied to both inbound and outbound risk management cases. In inbound risk management case, the critical sub-network identified consists of a supplier and five plants. In this case, “inbound PF ratio” and “total holding cost” are considered as effectiveness and efficiency measures, respectively. Under this setting, supplier flexibility and safety stock levels yielding the best supply chain performance are determined in risk mitigation phase. In outbound risk management case, the critical sub-network consists of two suppliers, a plant, and a customer. In this case, performance measures considered are “inbound PF ratio”, “outbound PF ratio” and “total holding cost”. Under this setting, the best demand forecast adjustment factor, supplier flexibility and safety stock levels are specified by considering supply chain performance measures.

In risk mitigation phase, the results obtained from the proposed multi-objective simulation-based optimization algorithm (MODE/D) is compared with current operating condition of the supply chain and the results obtained from NSGA-II. In both inbound and outbound risk management cases, MODE/D yields better results than the current operating condition and NSGA-II. Moreover, as MODE/D is a multi-objective optimization algorithm, several Pareto-optimal solutions are obtained. Therefore, managers of the supply chain can choose a suitable solution to their strategy from several alternative solutions. This characteristic of the proposed algorithm provides the flexibility in decision making under different supply chain competition environments.

Furthermore, the proposed DSS consists of a risk monitoring and control phase in which supply chain performance is monitored continuously and new risk management solutions are generated if it is needed. In case of a change in supply chain management strategy, a more suitable alternative solution among Pareto optimal solutions to the new strategy can be applied. In case of a major change in supply chain environment, risk identification, assessment, and mitigation phases of the DSS can be reiterated.

CHAPTER FIVE
CONCLUSIONS

In this thesis, a DSS is developed for SCRM by considering premium freights. The proposed DSS covers the risk management phases, namely, risk identification, risk assessment, risk mitigation, and risk monitoring and control. In risk identification phase, the risks affecting supply and delivery processes of the supply chain are identified and quantified through statistical models. In risk assessment phase, the supply chain is decomposed into material-level or product-level sub-networks according to the decision maker’s preference. To identify the critical material or product, TOPSIS technique is used. In the risk mitigation phase, the sub-network related to the critical material or product is modeled. To determine the parameter levels yielding the best supply chain performance for risk mitigation strategies, a multi-objective simulation-based optimization framework is developed. The simulation model of the critical sub-network constitutes simulation phase of the proposed framework. For the optimization phase of the framework, MODE/D is developed. Finally, in the risk monitoring and control phase, the supply chain performance and environment is monitored continuously. If a substantial change in supply chain performance or environment is faced, risk identification, assessment and mitigation phases can be reiterated.

The proposed DSS is implemented to an automotive supply chain spread on Europe. The company associated to the supply chain is a leading global supplier of electrical and electronic distribution systems in automobiles. The plants owned by the company assemble the components supplied from their suppliers into a semi-finished product. As the customers of the company are just-in-time automobile manufacturers, backordering is not allowed. However, the plants are subjected to inbound and outbound risks, such as delivery loss, delivery delay and demand variability. Consequently, in case of a shortage or delay risks, the plants have to receive materials or deliver products by a premium freight. As premium freights are last minute deliveries transported by airlines, they incur very high costs in a short time frame. Therefore, the company aims to reduce the premium freights. To reduce the premium freights, production quantities and safety stock levels should be increased. However, these actions result in high inventory holding costs. Therefore, the problem is handled under a multi-objective setting in which the objectives are minimization of annual holding cost and premium freight ratio.

The DSS is applied to inbound and outbound risk management cases for the supply chain. In the inbound risk management case, supply chain risks are identified as delivery loss, delivery delay, and material consumption variability. In risk assessment phase, the critical material and the sub-network related to the critical material are determined. In addition, in risk mitigation phase, the supplier flexibility and safety stock levels yielding the optimum holding cost and inbound premium freight are specified by the proposed simulation-based optimization framework. The results obtained by the proposed MODE/D are compared with current operating condition of the supply chain and the results obtained by NSGA-II. According to the results, MODE/D offers better results than NSGA-II and the current performance of the supply chain.

In outbound risk management case, the supply chain risks are specified as delivery loss, delivery delay and customer demand variability. In risk assessment phase, the critical product and the sub-network related to the critical product are determined. In risk mitigation phase, the demand forecast adjustment factor, supplier flexibility and safety stock levels yielding the optimum holding cost, inbound and outbound premium freight performances are specified by the proposed simulation-based optimization framework. The results are compared with the current performance of the supply chain and the results obtained by NSGA-II. The results reveal that the MODE/D yields better results compared to NSGA-II and current performance of the supply chain.

5.1 Contributions of the Thesis

The proposed DSS consisting of risk identification, risk assessment, risk mitigation, risk monitoring and control phases provides a comprehensive decision support for SCRM unlike the majority of the studies in this field. The proposed DSS is a reliable and realistic tool as it uses quantitative data in risk assessment and employs statistical risk models relying on real historical data in risk mitigation. Additionally, it is flexible in determining the focus of risk management and can be used in case of a change in supply chain management strategy or supply chain environment.

The proposed DSS is applicable for both inbound and outbound risk analysis. This provides flexibility to supply chain managers in deciding the focus of SCRM through their supply chain performance objectives. Additionally, the proposed DSS enables managers in combining redundancy and flexibility strategies to ensure both effectiveness and efficiency objectives in SCRM. The results of both inbound and outbound risk analyses reveal that the proposed DSS can suggest favorable risk mitigation solutions in terms of both efficiency and effectiveness objectives. Quantitative studies considering efficiency and effectiveness related objectives together in SCRM field is scarce. Therefore, this thesis contributes to the related literature in this regard.

In this thesis, premium freight is used an effectiveness measure for SCRM. As stated previously, there exist only two studies relating expedited shipping to SCRM. Additionally, total cost is the most widely utilized performance measure in supply chain inventory management, and there exist a few studies considering the problem under multi-objective setting until recent years. Furthermore, there exists no study considering premium freight as a performance measure in supply chain inventory management field. This thesis bridges this gap, since premium freight is used as an additional objective to the cost objective.

5.2 Suggestions for Future Research

There exist a number of possible research directions to extend this thesis. Firstly, risk drivers related to the inbound and outbound risks can be investigated. Additionally, a forecasting model that constitutes a risk alert mechanism can be integrated to the proposed DSS for proactive risk management. Moreover, the risks related to rare and severe events can be modeled, and extreme cases can be considered in the proposed DSS. Furthermore, external risk factors such as macroeconomic, social, and political risks can be modeled quantitatively.

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