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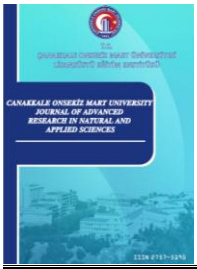

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An Integrated Risk Management Framework for Global Supply Chains

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Research Article

Abstract − In this study, a risk management framework is developed to support risk management decisions in global supply chains. The proposed framework covers all phases of risk management, namely, risk identification, risk mitigation and control. In the risk identification phase of the framework, the supply chain is decomposed into either material-level or product-level sub-networks according to the decision maker's preference. Afterwards, the most critical sub-network is modelled to evaluate different risk mitigation strategies. In particular, a combination of redundancy and flexibility strategies is considered for risk mitigation. These strategies are evaluated by simulation models in terms of their effectiveness and efficiency. While inventory holding cost is used as efficiency measure, effectiveness of the strategies is measured by premium freight ratio. The proposed framework provides a comprehensive and reliable decision support since it covers all phases of risk management and relies on quantitative data, and statistical analysis in risk modelling. Moreover, it is flexible as it can be easily adapted to any change in supply chain environment and strategy. In order to show the applicability of the framework, a practical demonstration is presented for a European automotive company. The results indicate that the proposed framework improves the supply chain performance in terms of efficiency and effectiveness.

Keywords − *Premium freight, simulation, supply chain risk management, TOPSIS,*

1. Introduction

As a result of the advances in communication and transportation technologies, today's supply chains have geographically expanded. This fact drives inter-firm competition into global scale. Consequently, supply chains adopt lean principles, and partners in supply chain become more connected to gain cost advantage. However, these strategies make supply chains vulnerable in terms of supply chain risks. Today, an adverse event affected a supply chain partner can influence the entire chain. Therefore, supply chain risk management (SCRM) has gained importance in both industry and academia. Nowadays, firms must evaluate interdependencies in their supply chain, identify their risks and measure likelihoods, effects and severities of the identified risks. Firms should develop risk management plans to avoid, mitigate or control the identified risks (Tummala and Schoenherr 2011).

In global supply chains, SCRM is challenging due to the complex supply chain structures and interrelationships. 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 subsystems. In addition, 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, SCRM should mainly rely on quantitative data to perform more realistic and reliable risk analysis.

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This study proposes an integrated SCRM framework for operational supply chain risk management in global scale. The proposed framework covers all phases of risk management, namely, risk identification, risk mitigation, risk monitoring and control phases. Particularly, the framework involves a risk identification phase in which the supply chain is decomposed into material-level or product-level sub-networks according to the decision maker's preference. Afterwards, risk mitigation strategies are simulated for the specified critical sub-network, and the best factor levels for risk mitigation strategies are determined by an experimental design approach. 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 the flexibility strategy. These strategies are considered in combined manner and evaluated in terms of both efficiency and effectiveness. Herein, the annual holding cost of the supply chain is employed as a measure of efficiency. In addition, the ratio of premium freights to regular orders is used to measure the effectiveness of the strategies. Specifically, in case of a shortage or delay risk, requesting a premium freight is an effective contingency strategy. However, premium freight is a type of last-minute shipment transported by airlines. It incurs very high costs to the responsible agent in a short time frame due to its setup cost and transportation mode. Additionally, it is an indicator of vulnerability of the supply chain. Hence, premium freight is used as an additional performance measure in this study to measure the effectiveness of the strategies.

The proposed framework consisting of all phases of SCRM provides a comprehensive decision support for SCRM unlike the majority of the studies in this field. The proposed framework is a reliable and realistic tool as it uses quantitative data and employs statistical risk models relying on real historical data. Additionally, it is flexible in determining the focus of risk management and can be easily adapted to any changes in supply chain management strategy or environment. Furthermore, to our knowledge, premium freight is used as an effectiveness measure for the first time for risk mitigation strategies in SCRM field.

The rest of the paper is organized as in the following. In Section 2, related studies in literature are overviewed. In Section 3, the proposed framework is presented. Section 4 presents an application of the proposed framework to an automotive supply chain. In Section 5, results of the application are discussed, and managerial implications are provided. Section 6 concludes the study.

2. The Related Literature

As SCRM is still an emerging research field, definition of risk concepts and risk mitigating strategies are still unclear. Therefore, several review studies such as (Singhal, Agarwal, and Mittal 2011), (Tang and Nurmaya Musa 2011), (Colicchia and Strozzi 2012), (Sodhi, Son, and Tang 2012), (Rangel, de Oliveira, and Leite 2014), (Heckmann, Comes, and Nickel 2015), (Ho et al. 2015) and Pournader et al. (2020) have been published with the aim of classifying the studies on SCRM. Additionally, the reader can find broad descriptions of risk concepts and risk management strategies in (Chopra and Sodhi 2004), (Christopher and Peck 2004), and (Sheffi 2005). In this section, recent quantitative studies related to SCRM field are presented.

The majority of the recent studies in the related field deal with the risk assessment phase of SCRM. In recent studies, multi-criteria decision making techniques, mathematical programming approaches, system analysis and simulation are utilized to assess supply chain risks. Among these approaches, multi-criteria decision making techniques are the most widely used tools in risk assessment. Wang et al. (2012) utilize a fuzzy analytical hierarchy process (AHP) model for risk assessment of implementing green initiatives in a fashion supply chain. Chaudhuri, Mohanty, and Singh (2013) utilize Failure Mode and Effects Analysis (FMEA) to prioritize the failure modes of vulnerable suppliers in new product development process. Chen and Wu (2013) propose an FMEA to categorize existing suppliers and select new suppliers by considering risk. Samvedi, Jain, and Chan (2013) utilize fuzzy AHP and fuzzy TOPSIS methods to obtain a supply chain risk index. Aqlan and Lam (2015a) propose a risk assessment framework which employs Bow-Tie analysis and fuzzy inference system for supply chains. In another study, Aqlan and Lam (2015b) quantify supply chain risks by Bow-Tie analysis, and select mitigation strategy by an optimization model. Govindan and Jepsen (2015) model supply chain uncertainties as intuitionistic fuzzy numbers and assess them via ELECTRE-C. Oliveira et al. (2022) identify and assess the supply chain risks of a home-care service provider via FMEA.

There exist a few mathematical programming applications in risk assessment context. Cardoso et al. (2015) develop a mathematical model for supply chain design and planning to assess resilience of alternative supply chain structures under different disruption types. Klibi and Martel (2012) propose a risk modelling approach considering random, hazardous and deeply uncertain events causing supply chain disruptions. They utilize a Monte-Carlo approach to assess the disruption impact based on the descriptive models.

Recently, system analysis and simulation approaches have become popular in risk assessment. Ghadge et al. (2013) develop a risk management framework by using systems approach to capture the dynamic characteristics of supply chain risks. Bueno-Solano and Cedillo-Campos (2014) investigate the impact of disruptions originated from terrorist acts via a system dynamics model. Wagner, Mizgier, and Arnez (2014) propose Monte-Carlo approach to evaluate possible losses due to disruptions in the US offshore oil industry. Guertler and Spinler (2015) demonstrate the criticality of the operational risks by using a system dynamics model that assesses the intra-organizational dynamics of risks.

In view of the related body of knowledge, it can be stated that the number of studies building comprehensive SCRM frameworks considering all phases of SCRM is limited. Among them, Giannakis and Louis (2011) propose a multi-agent based decision support system for supply chain disruption management. Schmitt and Singh (2012) analyse inventory placement and back-up strategies against supply chain risks by a simulation model. Carvalho et al. (2012) use a supply chain simulation model to evaluate the effects of mitigation strategies on performance of each supply chain entity under a set of scenarios. Rajesh and Ravi (2015) employ a grey-DEMATEL approach to investigate cause-effect relationships between supply chain risk mitigation strategies. Simchi-Levi et al. (2015) develop a SCRM framework for Ford Motor Company to identify new risks, evaluate proactive risk mitigation plans, and derive optimal contingency plans. Oliveira et al. (2019) propose hybrid and flexible simulation-based optimization models for SCRM. However, they do not present a real world application of their model. Kara et al. (2020) present an integrated SCRM framework which employs data mining algorithms. Talukder et al. (2021) propose a multi-indicator supply chain management framework that provides leanness, agility, sustainability, and resilience in the dairy business.

In this study, supply chain risks related to the physical flow in global supply chain networks are considered. In related literature, there exist a few study considering such large supply chain networks ((Chaudhuri, Mohanty, and Singh 2013), (Klibi and Martel 2012), (Wagner, Mizgier, and Arnez 2014), (Simchi-Levi et al. 2015)). As global supply chains consist of several facilities spread on several countries, risk management in these supply chains is challenging. A possible solution to overcome this challenge may be decomposition of the supply chain network into sub-networks by a risk assessment procedure as Chaudhuri, Mohanty, and Singh (2013) and Klibi and Martel (2012) do. Hence, in this study, the supply chain network is decomposed into critical sub-networks to according to their risk level. Unlike the previous studies, the proposed framework has a more comprehensive risk identification phase in which the supply chain can be decomposed into the single-product level or single-material level sub-networks. Therefore, the risks can be assessed at material or product-level by considering the preference of supply chain managers. Consequently, the proposed framework enables the flexibility essential for the real-world SCRM practices.

As stated previously, the proposed framework consists of a risk mitigation phase in addition to risk identification phase. In risk mitigation phase, redundancy and flexibility strategies are investigated to the aim of effective and efficient SCRM. In particular, 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 have been utilized in previous studies. However, they have not been evaluated from effectiveness and efficiency perspectives simultaneously. Effectiveness is the ability to achieve a predefined goal in case of adverse conditions. Efficiency is to ensure minimal spending of resources to reach the goal (Heckmann, Comes, and Nickel 2015). In this study, premium freight ratio and annual holding cost are utilized as effectiveness and efficiency measures, respectively. To the best of our knowledge, there exists no study in related literature considering premium freight as a SCRM performance measure.

3. The Proposed Supply Chain Risk Management Framework

In this study, an integrated SCRM framework is developed to support SCRM decisions by considering holding costs and premium freights. The proposed framework considers not only premium freights but also supply chain costs to ensure both effectiveness and efficiency objectives in SCRM. Moreover, the proposed framework covers all commonly acknowledged phases of SCRM namely, risk identification, risk mitigation and risk monitoring and control. Furthermore, the proposed framework has the flexibility in executing material or product-level risk analyses according to preference of the decision maker. The process flow diagram summarizing the phases of the proposed framework is illustrated in Figure 1. In subsequent sections, general process of the framework is explained through risk management phases.

3.1. Risk Identification

Firstly, the risks affecting supply and delivery processes of the supply chain are identified. Basically, supply chain risks can be classified into inbound and outbound risks by considering physical flow direction. 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 framework has the flexibility in focusing on the inbound or outbound risks. In this context, inbound and/or outbound risks are quantified according to the preference of the manager. In particular, the supply chain risks are quantified through statistical models developed by using past order, premium freight and customer sales data. The risk models are obtained by fitting the historical data to probability distributions.

Once the supply chain risks related to each agent are quantified, the most critical sub-network in terms of risk is identified. 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. In this context, the criteria for critical sub-network identification should be specified. In criteria determination, the adverse effects of risks related to the focal material or product and criticality of them should be considered. Hence, the critical sub-network identification stage involves multi-criteria decision making. Therefore, utilization of a multi-criteria decision making technique in this stage is appropriate. TOPSIS (Hwang & Yoon, 1981) is a suitable technique for this stage as it ranks the alternatives according to their criticality.

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

In particular, in identification of material or product-level sub-networks, 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.

The criteria weights are determined by using entropy weighting method (Deng, Yeh, & Willis, 2000). Entropy weighting method considers intrinsic information in each criterion, and does not require decision maker's judgment. In this sense, entropy weighting method is utilized to determine criteria weights to reduce human effort in decision making.

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 related to each criterion is calculated as follows.

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

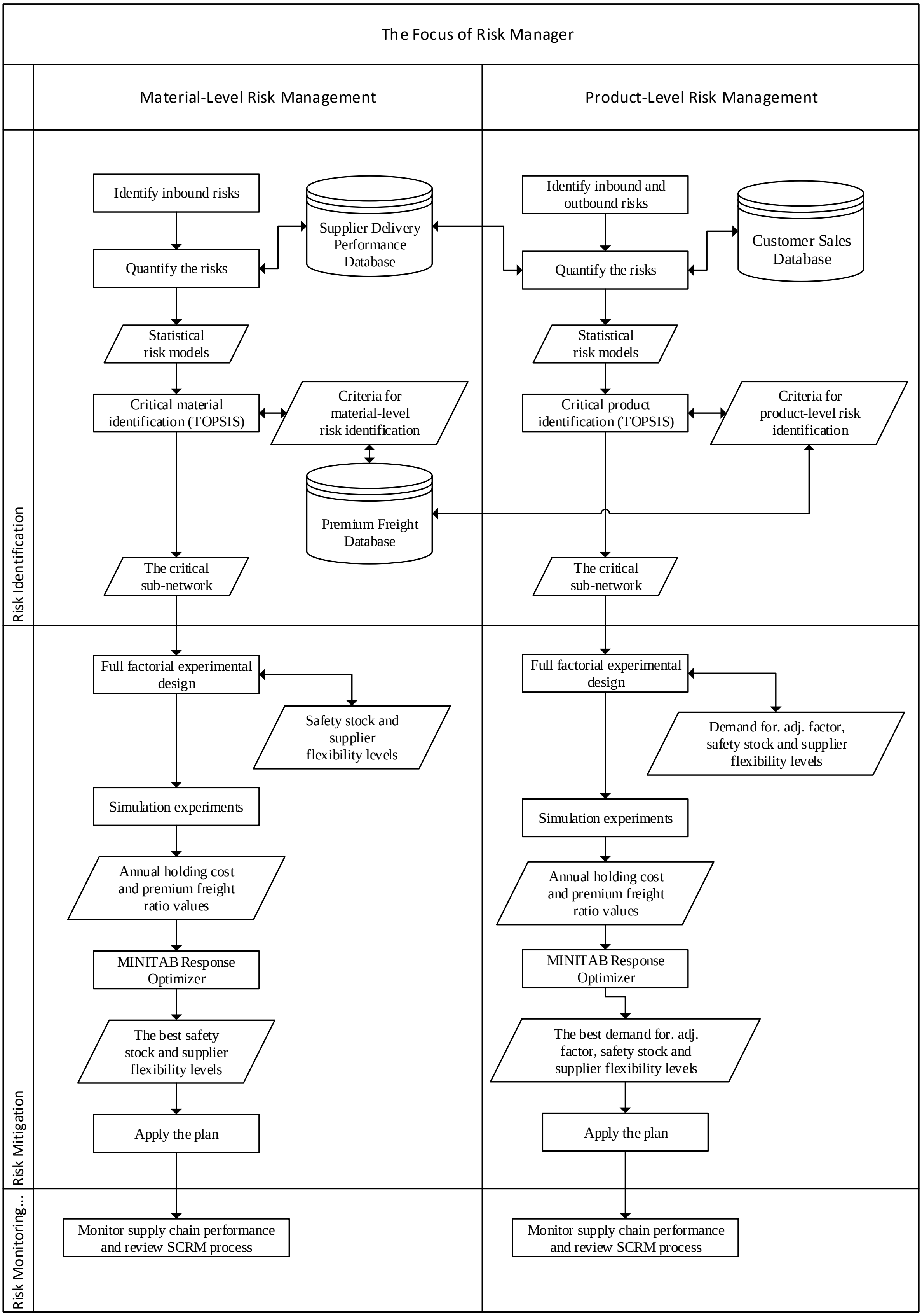

Figure 1. Process flow diagram of the proposed framework

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 the 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 framework, the overall criticality index obtained by TOPSIS present the criticality of material or product in terms of risk. The material (or product) with the highest level of overall criticality is identified as the most critical material (or product). The network related to the most critical material or product is specified as the critical sub-network. Afterwards, the critical sub-network is modelled to develop and evaluate risk mitigation strategies. Concept of the critical sub-network identification is illustrated with an example in Figure 2. An example supply chain system is demonstrated in Figure 2. In case of material-level analysis, the most critical material is identified as the material consumed by P1, P2, P3, and supplied by S2. Hence, the sub-network consisting of S2, P1, P2, and P3 is identified as the critical sub-network. Alternatively, in case of product-level 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).

3.2 Risk Mitigation

In this stage, a discrete event system 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 effectiveness and efficiency. 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 are 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 observe the effects of risk mitigation parameter levels a full factorial experiment is designed. Minitab Response Optimizer Tool is used to obtain the best parameter levels that give minimum annual holding cost and premium freight ratio.

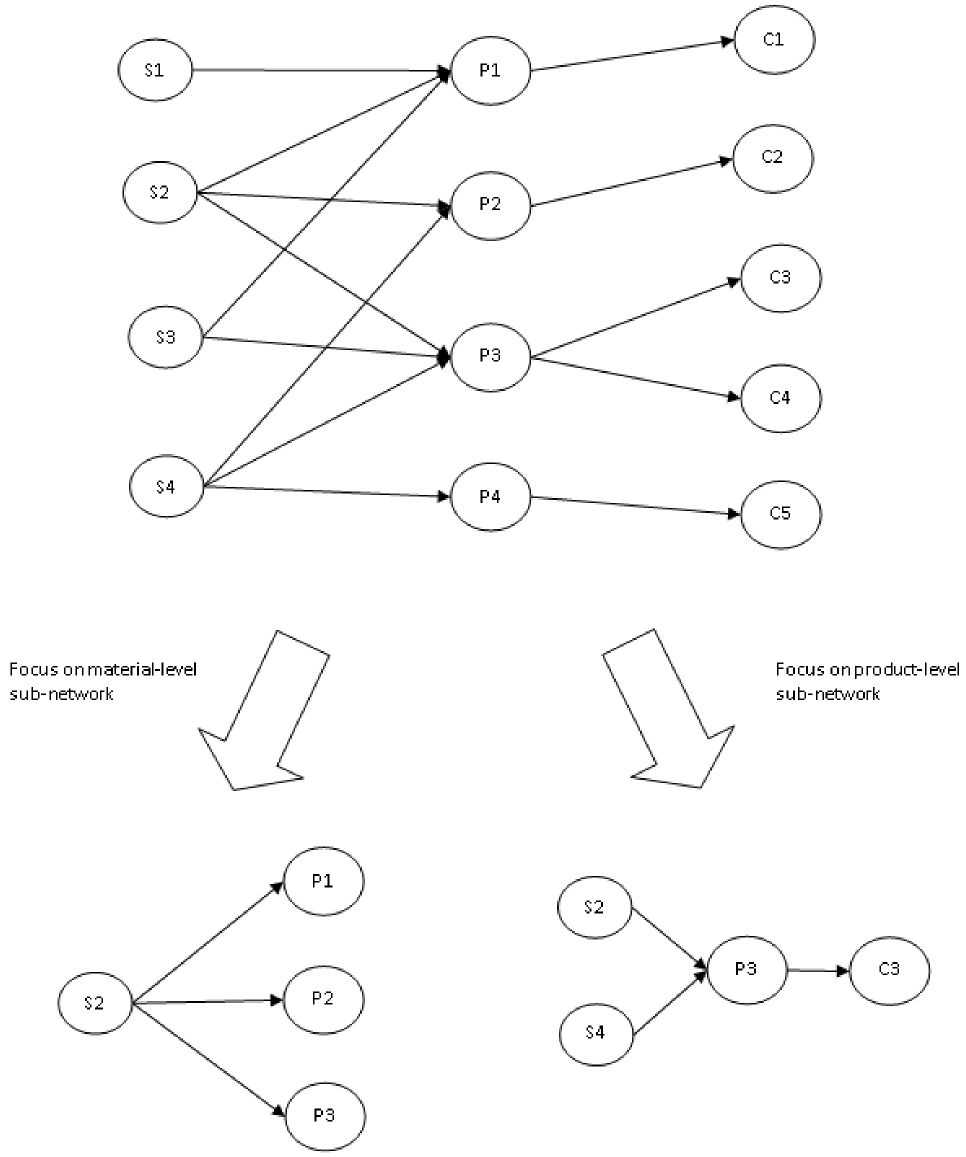

Figure 2. An example to critical sub-network identification

3.3 Risk Monitoring and Control

After the risk mitigation strategies are determined, outcomes of these strategies are continually monitored and reviewed. To ensure the continuous improvement in supply chain competitiveness, the management take actions in cases of any change in supply chain environment and risk levels. In particular, costs and premium freights related to the critical sub-network are continuously monitored. The supply chain manager can revise the mitigation plan according to the changes in critical sub-network performance. In a stationary supply chain environment, the manager will mainly focus on supply chain efficiency. In this case, the effects of low safety stock levels or low supplier flexibility on supply chain performance should be analysed. In turbulent environments, the manager will focus on keeping premium freights under control. Moreover, risk identification and mitigation phases can be reiterated in case of a major change in supply chain environment. Furthermore, the criteria for critical sub-network identification can be reconsidered.

4. Application of the Proposed Framework

The proposed framework is applied to a supply chain of a European automotive company. The supply chain consists of 752 suppliers, 12 plants and 55 customers. The plants assemble the materials into a semi-finished product specialized to the customer. 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.

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 forecast information by a demand forecast adjustment factor. In particular, customer demand forecast information is adjusted by multiplying it with demand forecast adjustment factor. The plants use the adjusted demand forecast information 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 for the materials' inventory. At the beginning of each week, the weekly requirements for each material are calculated. Then, if it is needed, an order is placed. The order quantities are determined by considering safety stock level, transportation lead time and average daily consumption of material, as well as, quantity flexibility limits of the suppliers. The orders are processed by suppliers immediately and are delivered after a transportation lead time. Shipments and deliveries are made only in working days. Production and storage processes of the suppliers are not considered in this study.

Inventory position of each plant is reviewed on daily basis. If inventory position of a material is below of the safety stock level and it is not the regular ordering day, an inbound premium freight must be requested from the supplier of the material. At the end of each week, customer demand is realized and filled from the inventory. The customer demand cannot be backordered. If it is not possible to deliver on time, final products are delivered to the customer by an outbound premium freight. The premium freights are delivered at the next day of the shipment.

The required data for the analysis are obtained from the plan for every part spreadsheets which are used by the plants for production planning. The demand forecast adjustment factor for each plant is 1.07. The plants holds 3.5 days of safety stock for each material. Supplier flexibility is presented as a percentage in the quantity flexibility contracts. In these contracts, $Fl\%$ flexibility means that the order quantity of a plant can be $Fl\%$ below or above of the contracted quantity. Currently, quantity flexibility of the suppliers is 50%. The quantity flexibility can be increased by making a new contract. However, the contracted unit price will be higher in case of a higher quantity flexibility. By consulting a supply chain manager, we model the relationship between supplier flexibility and unit price as in the following.

$$unit\ price^{new} = \left[\frac{100 + 20(Fl^{new} - Fl^{curr})}{100}\right] unit\ price^{curr} \tag{4.1}$$

where $unit\ price^{curr}$ is the current unit price under current quantity flexibility (Fl^{curr}), and $unit\ price^{new}$ is the new unit price which is specified for Fl^{new} quantity flexibility.

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

4.1 Material-Level Risk Management

This section focuses on the supply chain risks related to materials. Hence, the materials are investigated in terms of their criticality by the proposed risk identification 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 risk identification.

4.1.1 Risk Identification

The inbound risks of the focal supply chain are identified as supplier delivery delay and delivery quantity loss. The inbound risks are modelled by their occurrence and severity values. The fractions of late and under-shipped deliveries are obtained by historical 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 are obtained from historical order records. The historical data are fitted to a number of probability distributions such as normal, lognormal, exponential, Weibull and gamma distributions to obtain the risk models.

The outbound risk is identified as variability in the material consumption. However, since 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.

Afterwards, the focal supply chain is decomposed into a critical sub-network by considering inbound supply chain risk performance. The criteria for critical sub-network identification are determined by the supply chain manager as 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 the 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. In the TOPSIS, the decision matrices are normalized into [0,1]. Hence, the positive ideal solution (p_j) is one while the negative ideal solution (n_j) is zero for all criteria. In the calculation of overall criticality index, the criteria weights are obtained as 0.33, 0.33, and 0.34 for the number of premium freights, the monetary value of premium freights and the average weekly consumption, respectively. The overall criticality indices calculated by using TOPSIS are presented in Table 1. As it can be seen from the table, the most critical material is M1. The critical sub-network related to material M1 is presented in Figure 3.

Table 1
Overall criticality indices for 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		

4.1.2 Risk Mitigation

In this phase, a simulation model of the critical sub-network is developed. The inbound risks affecting the critical sub-network are modelled by the aforementioned risk quantification approach. The delivery loss probability is calculated as 0.05. To determine the probability distribution of the delivery loss quantity, the historical delivery loss data are fitted to a number of distributions in MINITAB statistical software. The best fitted distribution is a lognormal distribution with parameters 0.52 and 0.23. The delivery delay probability is 0.06. The delivery delay time distribution is specified as a lognormal (1.43, 0.46). By consulting the supply chain manager, material consumption variability distribution is specified as a uniform distribution varying between 50% and 150% of average daily consumption.

The performance measures are annual holding cost of supply chain and inbound premium freight ratio. Annual holding cost of supply chain involves annual holding costs of the plants associated with the critical material. Inbound premium ratio is the ratio of total amount of premium freights to total amount of orders associated with the critical material in the supply chain.

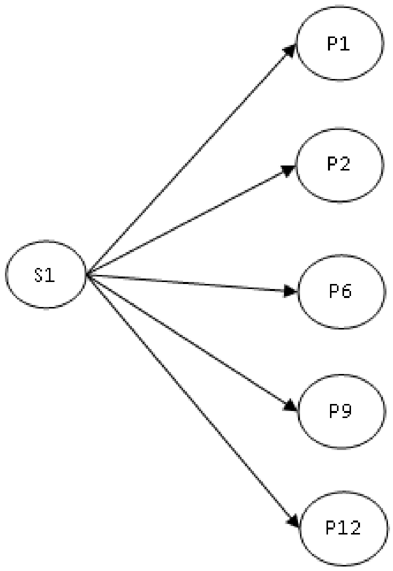

Figure 3. The critical sub-network identified in case of material-level risk management

The critical sub-network model is simulated for 104 weeks. The warm-up period is determined as two weeks by inspecting the variability in orders. Furthermore, required number of replications are determined by analysing the simulation outputs. In particular, a number of confidence intervals are calculated for annual holding cost and inbound premium freight ratio at the end of each replication. Until the confidence intervals become narrow enough, the replications proceed. The required half-length for the confidence intervals are 0.15. As a result, 15 replications are found to be sufficient to predict the performance measures within the predefined error rate.

To analyse the effects of risk mitigation strategies, a full factorial experimental design (Montgomery, 2008) is developed by considering five factor levels for safety stock and supplier flexibility (see Table 2). The response variables of the design are the annual holding cost and the premium freight ratio. The values for the response variables are obtained by the simulation model. According to the results of ANOVA, the effects of safety stock and supplier flexibility are significant on both annual holding cost and premium freight performances. To determine the best factor levels yielding minimum annual holding cost and premium freight ratio, MINITAB Response Optimizer tool is used. The best factor levels are determined as 4.5 days for safety stock and 30% for supplier flexibility. Comparison of the performances corresponding to the best factor levels and current factor levels is presented in Table 3. As one can see from the table, the new factor levels reduce the annual holding cost by 8% and the premium freight ratio by 3%.

Table 2
Factor levels considered in case of material-level risk management

Factors	Levels				
Safety stock	2.5	3	3.5*	4	4.5
Flexibility	30%	40%	50%*	60%	70%

*The current levels used in the supply chain

Table 3
Performance comparison in case of material-level risk management

	Safety Stock	Supplier Flexibility	Annual Holding Cost	Inbound Premium Freight Ratio
New factor levels	4.5	30%	€4015	0.19
Current factor levels	3.5	50%	€4349	0.20

4.2 Product-Level Risk Management

In this section, 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 deal with the risks associated with 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, 13 out of 2700 products presenting 80% of annual outbound premium cost are selected for risk identification.

4.2.1 Risk Identification

In the product-level risk management case, the inbound risks are identified as supplier delivery delay and delivery loss. The occurrence and severity values are quantified by the probability distributions derived from past order data as the in material-level risk management case. Outbound risks are identified as the customer demand variability and the deviation of actual customer demand from the shared demand information. These risks are modelled as ordinary variabilities that occur every week and only severity values of them are modelled. To model outbound risks, the demand data are obtained from the historical customer demand records.

Then, the focal supply chain is decomposed into a critical sub-network by considering outbound supply chain risk performance. By consulting the supply chain manager, the criteria for critical sub-network identification are determined as the number of outbound premium freights in previous year, monetary value of the outbound premium freights in previous year and average annual sales of the products. As in the material-level risk management case, the decision matrices are normalized into [0,1]. Therefore, the positive ideal solution is one and the negative ideal solution is zero for all criteria. The entropy weights are obtained as 0.34, 0.34, and 0.32 for the number of outbound premium freights, the monetary value of premium freights and the average annual sales, respectively. The overall criticality indices calculated by using TOPSIS method are presented in Table 4. 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.

4.2.2 Risk Mitigation

In this phase, a simulation model of the critical sub-network is developed. The bill of material information related to PR1 is reported in Table 5.

The inbound risks affecting the critical sub-network are modelled by the aforementioned risk quantification approach. The probability distributions that are best fitted to historical data are given in Table 6. The best fitted distributions are normal and Weibull distributions for delivery loss quantity and delivery delay, respectively. The customer demand is modelled by the demand forecast and the deviation of actual customer demand from the demand forecast. The best fitted probability distributions for the demand forecast and the deviation are Lognormal(6.27, 0.51) and Lognormal(0.07, 0.21), respectively.

The performance measures are annual holding cost of supply chain, inbound premium freight ratio, and outbound premium freight ratio. Annual holding cost and inbound premium freight ratio are calculated as in Section 4.1.2. Outbound premium freight ratio is the ratio of total amount of the premium freights related to the products to the total amount of products sold.

Table 4
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

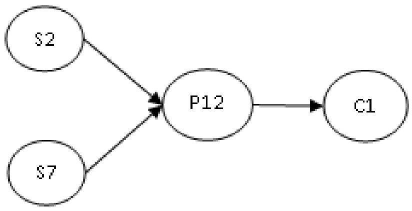

Figure 4. The critical sub-network identified in case of product-level risk management

Table 5
Bill of material for PR1

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

Table 6
The inbound risk model in case of product-level risk management

	Delivery Loss		Delivery Delay	
Suppliers	Probability	Quantity distribution	Probability	Time distribution
S2	0.05	Normal(0.45,0.17)	0.09	Weibull(1.65,1.61)
S7	0.03	Normal(0.51,0.25)	0.07	Weibull(1.20,2.30)

The warm-up period length and the number of replications are determined in the same manner described in Section 4.1.2. The critical sub-network model is simulated for 104 weeks and 15 replications. The warm-up period is specified as one week. To analyse the effects of risk mitigation strategies, a full factorial experimental design is developed for five factor levels for demand forecast adjustment factor, safety stock and supplier flexibility. (see Table 7). The response variables are the annual holding cost, inbound and outbound premium freight ratios. The response values are obtained from the simulation model.

Table 7
Factor levels considered in the experiment

Factors	Levels				
Demand adj.	1	1.03	1.07*	1.11	1.15
Safety stock	2.5	3	3.5*	4	4.5
Flexibility	30%	40%	50%*	60%	70%

*The current levels used in the supply chain

According to the ANOVA results, all the factors have significant effect on the holding cost and the outbound premium freight ratio. However, only the supplier flexibility affects the inbound premium freight ratio significantly. The best factor levels yielding minimum annual holding cost, inbound and outbound premium freight ratios are determined via MINITAB Response Optimizer Tool. The best factor levels are 1.15, 2.5 and 30% for demand forecast adjustment factor, safety stock and supplier flexibility, respectively. Comparison of the performances corresponding to these factor levels and current factor levels is presented in Table 8. The results reveal that the new factor levels reduce annual holding cost by 10%, inbound premium freight ratio by 26%, and outbound premium freight ratio by 28%.

Table 8
Performance comparison of in case of product-level risk management

	Demand Adj. Fac.	Safety Stock	Supplier Flexibility	Annual Holding Cost	Inbound Premium Freight Ratio	Outbound Premium Freight Ratio
New factor levels	1.15	2.5	30%	€20254	0.07	0.04
Current factor levels	1.07	3.5	50%	€22425	0.10	0.06

5. Discussion and Managerial Implications

According to the results, the proposed framework is capable of ensuring a substantial improvement in terms of holding cost and premium freight performances. In this application, emphasizing on redundancy strategies improves the supply chain risk performance in both holding cost and premium freight aspects. In Figure 5, the main effects of safety stock and supplier flexibility levels on holding cost and premium freight ratio are given for the material-level risk management case. The ANOVA results shows that the effects of supplier flexibility on annual holding cost and premium freight ratio are significant. Moreover, safety stock level has a significant effect on premium freight ratio. In this case, higher supplier flexibility levels yield lower premium freight ratio, but increase holding cost. On the other hand, main effects of safety stock levels on premium freight ratio is nonlinear where the current safety stock level (3.5 days) incurs the worst premium freight performance. Thus, a compromise solution can be obtained among two objectives by decreasing supplier flexibility level and increasing safety stock level. In accordance with this result, the proposed framework improves both holding cost and premium freight ratio by reducing supplier flexibility and increasing safety stock levels (see Table 3).

In Figure 6, main effects of demand forecast adjustment factor, safety stock, and supplier flexibility levels on supply chain performance are illustrated for product-level risk management case. According to the ANOVA results, demand forecast adjustment factor, safety stock and supplier flexibility have significant effect on annual holding cost and outbound premium freight ratio. Moreover, supplier flexibility has a significant effect on inbound premium freight ratio. As one can infer from the figure, demand forecast adjustment factor has lower effect on holding cost and higher effect on outbound premium freight ratio than the other parameters. Therefore, to reduce outbound premium freight ratio, demand forecast adjustment factor can be increased. Moreover, to reduce holding cost supplier flexibility can be reduced by considering its significant relationship with demand forecast adjustment factor in terms of outbound premium freight ratio. Furthermore, we can infer from the figure that safety stock has relatively low effect on outbound premium freight ratio. Accordingly, the proposed framework ensures better supply chain performance in three objectives by increasing demand forecast adjustment factor and decreasing safety stock and supplier flexibility levels (Table 8).

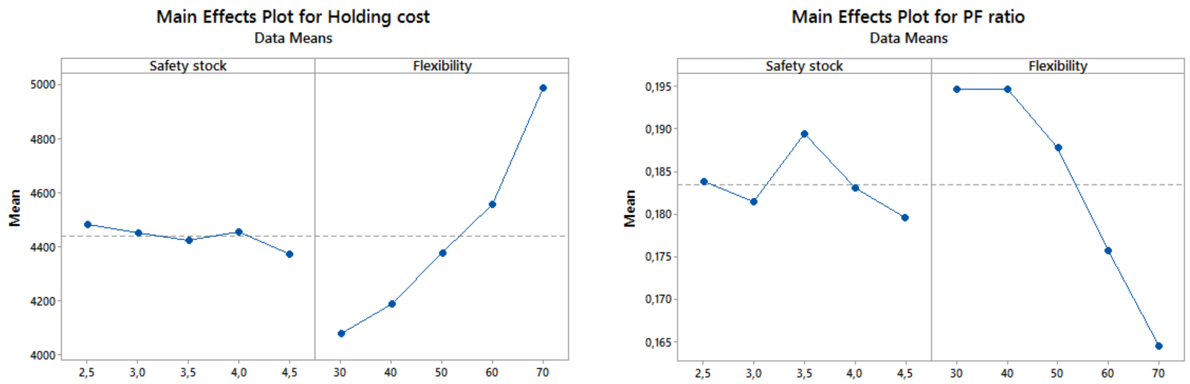

Figure 5. Main effects of parameter levels on supply chain performance in material-level risk management case

In both cases, the framework suggests lower supplier flexibility levels than the current levels. In material-level risk management case, safety stock levels are increased. In the product-level risk management case, demand forecast adjustment factor is increased. Consequently, redundancy strategies are preferred rather than flexibility strategy in this application. Therefore, the managers of the focal supply chain should put more emphasis on redundancy strategies (high demand forecast adjustment factor and safety stock levels).

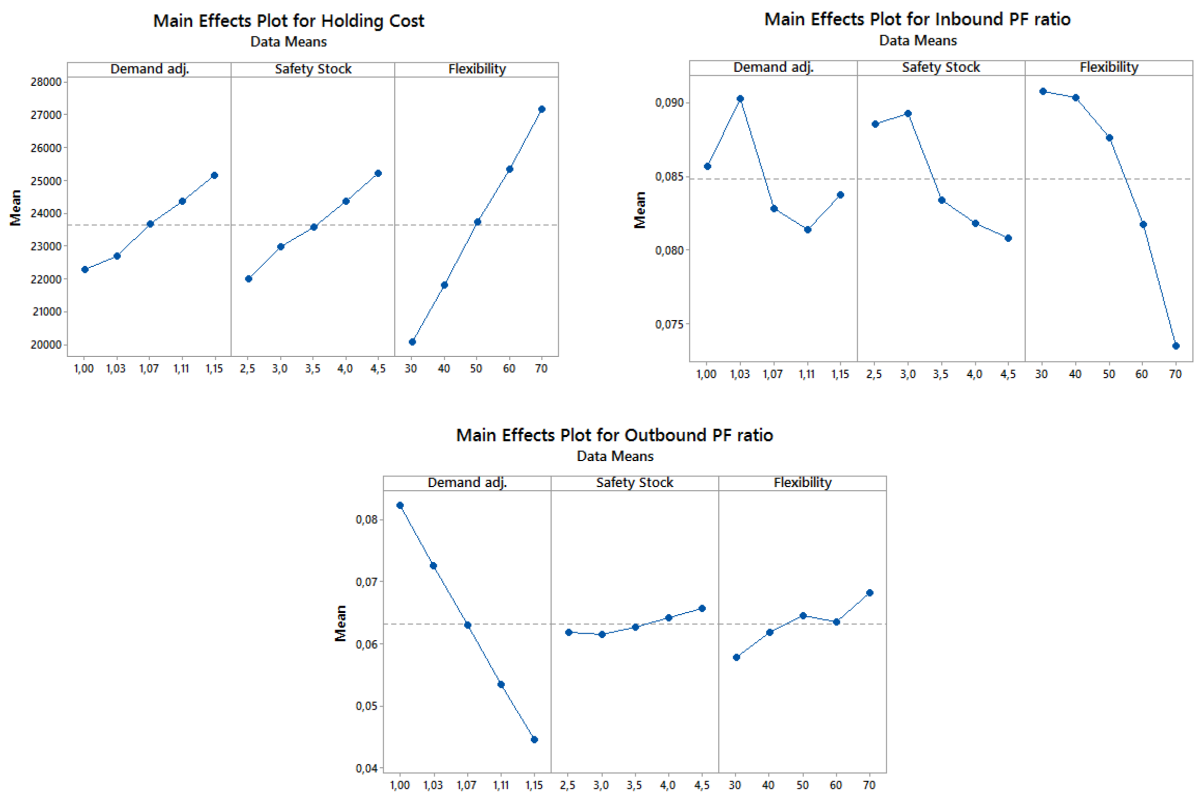

Figure 6. Main effects of parameter levels on supply chain performance in product-level risk management case

Supply chain managers can use the proposed framework in cases of any changes in supply chain environment, competition strategy, and new supplier contracts. Although the objectives have equal importance in this application, the proposed framework provides the flexibility in evaluating risk mitigation plans by considering different weights for the objectives. In a stable supply chain environment, the manager can give more importance to holding costs. In turbulent supply chain environment, the manager will mainly focus on supply chain risks and reduce premium freights. Moreover, in case of a change in competition strategy, the manager may consider reducing holding costs to gain cost advantage, or focus on supply chain risks to ensure customer satisfaction. Furthermore, the proposed framework will be beneficial in making new supplier contracts, since it considers both cost and resilience objectives.

The proposed framework provides a comprehensive decision support since it involves both material and product-level risk analyses through the preference of the decision maker. Additionally, it considers redundancy and flexibility strategies in combined manner to improve supply chain risk performance efficiently and effectively. Moreover, it measures the supply chain vulnerability by premium freight ratio. Furthermore, due to its flexible and convenient structure, it can be applied to various supply chain structures.

6. Conclusion

This study proposes an integrated risk management framework for global supply chains. In the risk identification phase of the proposed framework, global supply chain is decomposed into material-level or product-level critical sub-networks according to preference of the manager. Consequently, the proposed framework is applicable for both material and product-level risk analyses. This provides the flexibility in choosing the focus of SCRM through the manager's performance objectives. Additionally, the proposed framework enables managers in combining redundancy and flexibility strategies to ensure both effectiveness and efficiency objectives in SCRM. In this study, an application of the proposed framework to an automobile supply chain is presented. The results of both material and product level analyses show that the proposed framework improves the supply chain performance.

A limitation of this study is the assumption of the identical safety stock and supplier flexibility levels throughout the supply chain. These parameters may take different values for each material and supplier. However, this increases the complexity of the problem. Consequently, finding the best parameter levels by using an experimental design approach become challenging. Furthermore, analysis of supply chain risk drivers, and considering rare and severe adverse events in the proposed framework are possible future research directions.

Author Contributions

Mualla Gonca Avci: Conceptualization, Methodology, Software, Validation, Data curation, Writing

Conflicts of Interest

The authors declare no conflict of interest.

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