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A dynamic resilience management framework for deep-tier supply networks

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ABSTRACT

The unprecedented supply chain disruptions caused by COVID-19 has had severe operational and financial consequences to firms across industries and continents. While tactical reactionary strategies can help, firms are in need of proactive management approaches to design more resilient supply chain networks in the first place. Firms are looking for an effective framework to design and monitor supply networks, mitigate disruption consequences, and manage resilience under different scenarios. We propose a framework to manage the resilience of deep-tier automotive supply networks by integrating a simulation-based resilience assessment scheme for effectiveness with an efficient optimization-based framework to find optimal strategies for handling regular disruption events. The framework promotes network analysis techniques combined with discrete-event simulation informed by secondary data sources and global supply risk databases for improving resilience management. We validate the effectiveness of the proposed framework using a real-world global automotive original equipment manufacturer case study. Our results demonstrate that the proposed dynamic framework relying on deep-tier visibility can optimize resilience strategies through all key performance indicators. The results show an average of 35% and 40% reductions in back-ordered cost and shipment delays, respectively, with a marginal growth in holding cost when the proposed framework is implemented with deep-tier visibility.

1. Introduction

Modern supply chains are large-scale systems with hidden vulnerabilities due to the complexity of deep-tiered supplier networks, global competition, escalating customer expectations, and climate change. All organizations within these networks (retailers, manufacturers, and suppliers) are being forced to cope with many unforeseen events. According to McKinsey research, global supply chain shocks with high severity are occurring more frequently (George, 2021). For instance, unexpected disruptions lasting a month seem to happen every 3.7 years, resulting in financial losses reaching 45% of annual company earnings. The current coronavirus outbreak decimated global supply chain flows and activities, causing a global shortage of even the most basic consumer goods (Azcue et al., 2020). Two years on, these shortages continue to create severe anxiety for majority of the firms. Compounded by semiconductor chip shortage, automakers continue to regularly halt their production in several factories across North America (Earle, 2021). The 2020 Texas winter storm caused unexpected long shipping delays throughout many supply networks for months (Shirley, 2021). An 2016 explosion at a BASF factory in Germany created considerable shortage of raw materials in many global supply chains (Macdonald, 2016).

Globalization and increasingly unstable environment (resulting from both man-made and natural disasters) makes supply network resiliency a fundamental requirement for business continuity, because only resilient companies can quickly respond and return to normalcy under disruptions. A 2020 McKinsey survey verified that 93% of supply chain leaders are expected to increase supply network resilience by relying on increased dual sourcing, inventory levels, and through near-shoring strategies (Knut et al., 2020). The COVID19 pandemic revealed the importance of 'visibility' into both the demand and supply sides to minimize disruptions while improving productivity (George, 2021). Recently, Taghizadeh et al. (2021) demonstrated through an automotive case study that visibility into the deep-tiers of supply networks is key to effective resilience assessment. However, it is important to proactively address resilience during the network (re) design in the first place (Basole and Bellamy, 2014; Mubarik et al., 2021).

Supply network resilience management is drawing more attention in recent years from both academics and firms (Rahman et al., 2018;

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Fattahi et al., 2020; Taghizadeh et al., 2021; Kamalahmadi et al., 2021; Ellingrud, 2020; Lund, 2021). Tomlin (2006) illustrates that pre-disruption mitigation strategies can be considered to design a resilient supply network and alleviate the negative consequences of disruptions. However, many organizations are unable to create proper and dynamic procedures for the post- or pre-disruption management (Fattahi et al., 2020). In addition, COVID19 illustrates that a comprehensive view of the supply network through deep-tier visibility is crucial to identifying hidden risks and mitigate disruption outcomes. McKinsey's research reported that it is rare for large firms to collaborate with their tier-1 suppliers to understand the risks stemming from tier-2 and deeper-tier suppliers (Lund et al., 2020). In a fast-changing and complex environment, it is time to re-imagine resilience management by considering higher visibility into the deeper-tiers of supply networks to minimize the risks, costs, and improve the performance of supply networks.

Numerous methods have been proposed for supply chains resilience management and can be broadly categorized into two classes based on quantitative resilience approaches employed: 1) optimization-based (Govindan et al., 2017) and 2) simulation-based (Stefanovic et al., 2009). In recent years, the research studies have sought to integrate these methods for more effective resilience management. Employing simulation-based optimization methods allow business leaders to more confidently develop and deploy effective solutions to the range of possible disruption scenarios they may face. Furthermore, business leaders can simulate stress-tests within the supply network to ensure their strategies can succeed in a range of future scenarios (Tordecilla et al., 2021). In practice, the implementation of simulation-based optimization methods is still rare in supply chain resilience management, and there are still opportunities to extend this area.

The key contributions of this study are as follows: (1) While numerous studies have focused on two-level supply chain networks to manage resilience and develop mitigation strategies (Li et al., 2020; Liu et al., 2023; Song et al., 2024; Narassima et al., 2024), this research advances the existing literature by proposing a dynamic resilience management framework tailored for deep-tier supply chains. This model also serves as an effective resilience management tool for complex supply chain networks with multiple tiers; (2) the presentation of a discrete-event simulation-based optimization framework leveraging historical and secondary data sources to assess and optimize focal firm resilience; and (3) the introduction of regression models as surrogates to efficiently represent the impact of supply chain decisions on resilience, addressing the computational expense of simulation-based optimization through RMSE-based slack constraints; (4) the demonstration of optimal resilience management by jointly allocating safety buffers across the network, such as capacity and inventory levels, rather than applying static rules that are independent of the nodes and arcs in the supply chain network. We validate the framework by relying on experiments derived from a real-world case study at a leading global automotive original equipment manufacturer (OEM). The results demonstrate the critical role of high transparency and visibility into deep-tier supply chains for dynamic and efficient resilience management. The proposed framework is general and can be adapted to various supply networks including pharmaceutical, electronics, and automotive industries, where the goal is to optimize network resilience cost-effectively.

The rest of this paper is organized as follows: Section 2 reviews the related supply chain resilience management literature. Section 3 describes the proposed resilience management framework. Section 4 illustrates the details on surrogate modeling to optimize supply chain resilience combined with regression and discrete event simulation with disruption settings. Section 5 presents results from a real-world case study. Finally, Section 6 provides some conclusions and directions for future research.

2. Literature review

Resilience is a multi-dimensional concept that originated in psychology, social, organizational, and ecological sciences and has since expanded into supply chain management (Lohmer et al., 2020; Pettithmer et al., 2020; Kumar and Kumar, 2024; Narassima et al., 2024; Vali-Siar and Roghanian, 2024). It refers to a system's capacity to anticipate and recognize unanticipated events and risks before they produce a negative impact. It illustrates how a system can quickly recover to a stable or improved condition when a disruption occurs (Woods, 2017). Tukamuhabwa et al. (2015) summarize the critical dimensions of supply chain resilience as the timely capacity to plan, respond, and revert to an original or more favorable state. Supply chain resilience is also seen as a network-level construct that arises in non-linear and dynamic ways through interacting suppliers' adopting various behaviors and connections (Wedawatta et al., 2010; Giannoccaro et al., 2020). Resilience can be categorized into two perspectives: static and dynamic. Static perspective refers to a resilience system if it can absorb disturbance and return to its original equilibrium state when shocks occur (Bhamra et al., 2011). On the other side, the dynamic perspective is the ability of a system to evolve and move over time to original or improved states (Carvalho et al., 2012; Massari and Giannoccaro, 2021).

Various supply chain resilience strategies, either proactive, reactive, or both, have been proposed in the literature to reduce risks and increase efficiency (Li et al., 2017; Kazancoglu et al., 2022; El Korchi, 2022). Contracting with backup suppliers, increasing inventory and capacity levels, leveraging information sharing, and implementing accurate demand forecasting are some of the most relevant resilience strategies (Ivanov and Rozhkov, 2017; Hosseini et al., 2019; Gholami-Zanjani et al., 2021). Recent studies emphasize the role of local supply chains, which were previously considered as a backup approach before COVID-19, and their relationship with resilience networks under various scenarios. The studies highlight how neglecting the balance between local and global decisions can alter strategic priorities (McDougall and Davis, 2024).Several empirical studies have been conducted and demonstrated the efficacy of resilience strategies. They found that as resilience capabilities grow and supply chain vulnerabilities decrease, supply chain resilience improves (Adobor and McMullen, 2018). Therefore, supply chain resilience assessment is critical for leaders to evaluate the current resilience strategies and take future actions for improvement. The notion of 'resilience triangle' has been introduced by Henry and Ramirez-Marquez (2012) to measure the resilience of a system. Zhang et al. (2018) applied the resilience triangle concept to quantify resilience for the designed network by defining a nonlinear function to describe the restoration behavior. The author proposed a resilience-based optimization formulation to maximize resilience while minimizing the cost of operations.

To design or redesign a resilient supply chain, many research studies utilized simulation (Munoz and Dunbar, 2015; Saif and Elhedhli, 2016; Ge et al., 2016) or analytical models (Dixit et al., 2016; Jabbarzadeh et al., 2018; Li et al., 2017) following optimization techniques. Various quantitative and qualitative 'metrics' have also been proposed for design a resilient network. For example, Cardoso et al. (2015) developed a mixed-integer linear model to build a robust network by adding 11 quantitative indicators. Soni et al. (2014) proposed 10 qualitative resilience indices to configure a resilience network through a game theory model. In addition to establishing an efficient approach for supply chain resilience management, simulating random and targeted scenarios have been considered for optimization models (Ivanov, 2021; Adobor and McMullen, 2018; Taghizadeh et al., 2017). Gholami-Zanjani et al. (2021) propose a comprehensive stochastic optimization approach to enhance the resilience level of the food supply chain by defining a number of resiliency strategies and generating plausible scenarios to evaluate their model. Fjørtoft et al. (2023) suggest a two-stage stochastic optimization model with six mitigation strategies to minimize disruption costs and CO2 emissions, emphasizing data-driven resilience for optimizing multi-stage green supply chain performance. Alikhani et al. (2021) evaluate multiple strategies to design or redesign the resilience of retail supply chains using a stochastic optimization model, considering both post- and pre-disruption scenarios. They demonstrate a meaningful trade-off between resilience and cost efficiency by evaluating the impact of random and targeted disruption scenarios on their framework using simulation combined with optimization.

Simulation-based optimization is an appealing integrated strategic approach and a valuable tool for decision-makers who wish to determine which combination of parameters and input configurations will result in an optimal system performance (Yoo et al., 2010). In a recent review paper, Tordecilla et al. (2021) highlighted the benefits of employing simulation-based optimization methods in supply chain resilience management. The author recommended considering hybrid approaches and surrogate models combining simulation and machine learning as future research opportunities. Additionally, Saisridhar et al. (2024) emphasized the need for supply chains to develop responsiveness, resilience, and robustness to manage disruptions while staying competitive. Their study recommends using hybrid, online, and physical simulations to model social-ecological aspects and risks, enabling effective mitigation strategies amid increasing disruptions. Mele et al. (2006) presented a unique approach for dealing with supply chain management with demand uncertainty by a large-scale mixed-integer nonlinear problem utilizing discrete event simulation-based optimization. However, we are lacking studies implementing simulation-based optimization for designing resilient supply networks while using different scenarios.

Motivated by these studies, this paper extends the literature to address the following gaps. First, we consider the deep-tier visibility to resilience management, and optimize the recovery and mitigation strategies informed by secondary data sources. Second, we assess the resilience of the supply network by integrating discrete event simulation and optimization formulation. Finally, we demonstrate how utilizing the secondary data sources with deep–tier visibility can generate a more actionable and resilient and cost efficient network.

3. Methodology

This research study proposes an effective resilience management framework to optimize the mitigation strategies for a deep-tier supply chain network. The simulation-based optimization approach is used in the proposed framework, shown in Fig. 1. The main steps of the resilience management framework are as follows:

- **Formulate Optimization Model:** Define the optimization model by specifying the objective function and decision variables related to the network. Solve the model to obtain optimal values (refer to Section 4.1).
- **Design of Experiments (DOE):** Generate initial sample points using DOE principles to aid decision-makers in understanding the system and process functionalities (Longo and Mirabelli, 2008; Kleijnen, 2005) (see Section 4.1.1).
- **Simulate and Assess Resilience:** Use the optimal values obtained from Step 1 and the data samples from Step 2 to simulate the deep-tier supply chain network. Assess the network's resilience. If the focal firm's resilience level does not meet the target, revise the current mitigation strategies (refer to Section 4.2.2).
- **Surrogate Modeling:** Develop a surrogate linear regression model to estimate the relationship between decision variable values (from Step 1) and the resilience levels of each tier-1 supplier (from Step 3) (see Section 4.3).
- **Refinement and Reassessment:** Incorporate the linear regression models as new constraints into the original optimization problem defined in Step 1. Solve the updated problem to obtain new optimal values. Use these updated decision variables to run simulations in Step 3 and assess resilience levels. If the focal firm's resilience still does not meet the target, repeat the process until the target resilience level is achieved (see Sections 4.3.1 and 4.3.2).

3.1. Supply chain network

Recent research studies (Dubey et al., 2020; Dong et al., 2022; Ivanov, 2018) highlighted how a high level of transparency and visibility through supply chain networks could improve resilience management and reduce the negative consequences of disruption with affordable cost and acceptable recovery time. In this study, we analyze and simulate a deep-tier supply chain network based on a real-world automotive industry informed with secondary data sources. Supply chain network structures consisting of a focal firm (OEM), suppliers in three tiers, their connections, and related policies following the same networking setting were suggested by the study in Taghizadeh et al. (2021). The focal firm can be a global automotive original equipment manufacturer (OEM) or final assembly plant for this research study. The tier-3 supply network includes suppliers, warehouses, transportation modes, inventory, and

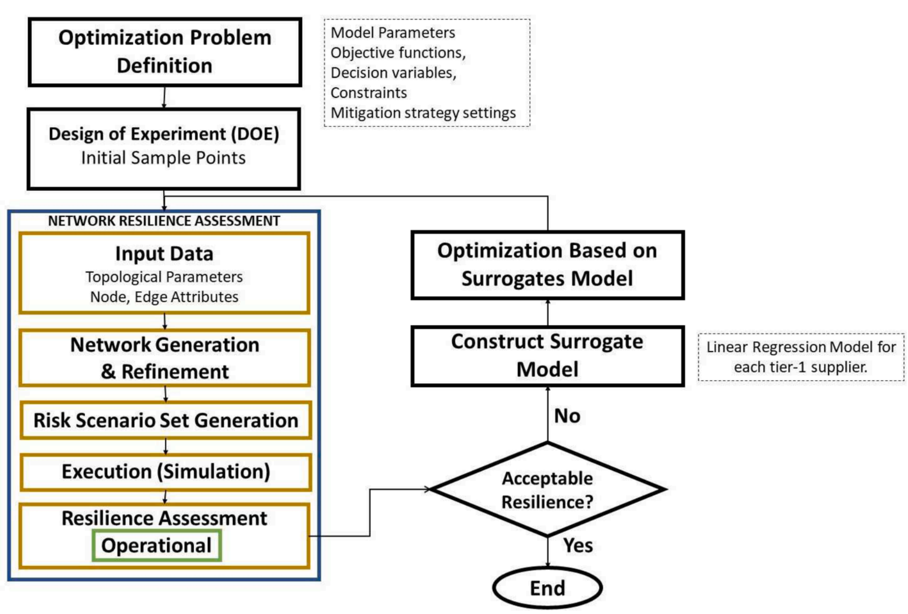

Fig. 1. Simulation-based optimization framework.

shipping policies information.

The nature of supply chain resilience management is multi-dimensional, and there are different ways to measure and assess the impact of short- or long-term disruptions (Zhang et al., 2018; Carvalho et al., 2012). The proposed resilience management framework is well suited for all available performance metrics such as service level, lead time, capacity utilization, etc. In this research, the lost demand or fill rate that is frequently cited in the literature is applied as the performance metric (Taghizadeh et al., 2021; Craighead et al., 2007). Disruption in supplier location, production, and transportation may reduce the availability of the final product for the customer, and the final focal firm such as OEMs and retailers could not be satisfied for customer demand. Let R_n and $R_n(t)$ denote the total resilience and the resilience at time t for each network component; since the performance metric describes the ratio of lost demand at each component, then resilience for each component can be expressed as follows:

$$R_n(t) = 1 - \frac{LD_n(t)}{TD_n(t)}, \qquad \forall n \in N, t \in T. \tag{1}$$

$$R_n = \frac{\sum_{t=0}^{T} R_n(t)}{T}, \qquad \forall n \in N. \tag{2}$$

In the above equations ((1), (2)), T is the duration of the planning horizon, and N is the set of nodes for a given supply network. In (1), $LD_n(t)$ and $TD_n(t)$ denote the lost and total demands at supplier n and time period t.

3.2. Strategies

Typically, automotive companies conduct market analysis to determine the qualified suppliers, and then use one supplier who can offer good quality at a competitive unit price and with low tooling costs (Sanci et al., 2022). In addition, the company can prefer to have single sourcing and sign a contract with one supplier for an easy implementation of just-in-time (JIT) production. However, when any disruption occurs in the future, the company will be exposed to the risk of satisfying demand due to delay in delivery from the single supplier or even due to a temporary shutting down. Therefore, different mitigation strategies should be opted to fit the characteristics and needs of the company (Kleindorfer and Saad, 2005). The proposed resilience management framework incorporates the following mitigation strategies, enabling a resilient and robust network for the automotive industry:

- The company can mitigate disruption at the primary supplier location by holding an extra capacity regardless of single or dual sourcing. However, there is a limitation to excess inventory at the primary supplier location.
- The company can sign a contract with a secondary supplier and order parts only when the primary supplier is disrupted. It means that when the primary supplier fails to deliver parts, pre-qualified secondary supplier can cover the backorders based on its capacity permits. However, the secondary supplier will need time to prepare and starts production.
- The company can sign a contract with a backup supplier. For instance, the company can invest in working with a more reliable supplier with minimum risk. When the primary supplier's operation is disrupted, and the secondary supplier could not cover the backorder, the backup supplier can deliver the required parts after preparation.

4. Implementation

This section presents details on simulation-based optimization steps to develop a dynamic supply network resilience management in practice. The details of optimization formulation and simulation with related parameters have been discussed. In addition, the following section describes the proposed surrogate model and its details.

4.1. Optimization formulation

Based on the proposed framework in Section 3, a mathematical formulation for risk mitigation is developed to minimize total strategic costs of the entire supply chain network. An overview of notation used throughout the proposed model is present in Table 1.

$$Min \quad \sum_{k\in K}\sum_{j\in J}(f_{kj}v_{jk} + q_{kj}l_{kj}) + \sum_{k\in K} r_k\psi_k D a_k + \sum_{k\in K} c_k e_k + \sum_{k\in K} b_k z_k + \sum_{k\in K} h_k s_k \tag{3}$$

Subjectto :

$$x_k + y_k = 1 \qquad \forall k \in K \tag{4}$$

$$\psi_k D x_k \leqslant \sum_{j\in J} w_j v_{kj} \qquad \forall k \in K \tag{5}$$

$$v_{k1} \leqslant n_{k1} \qquad \forall k \in K \tag{6}$$

$$v_{kj} \leqslant n_{kj-1} + n_{kj} \qquad \forall k \in K, j \in 2, \ldots J-1 \tag{7}$$

$$v_{kJ} \leqslant n_{kJ-1} \qquad \forall k \in K \tag{8}$$

$$\sum_{j\in J} v_{kj} = 1 \qquad \forall k \in K \tag{9}$$

$$\sum_{j\in J} n_{kj} \leqslant 1 \qquad \forall k \in K \tag{10}$$

Table 1
Nomenclature.

Sets	
K	Set of distinct parts, indexed by $k \in K$
J	Set of discount breakpoints, indexed by $j \in J$.
Variables	
x_k	Capacity for part k at primary supplier, as a fraction of D
s_k	Safety Stock for part k at primary supplier, as a fraction of D. (D expected daily demand for the planning horizon)
e_k	Binary variable indicating the selection of a secondary supplier for part k
y_k	Capacity for part k at secondary supplier, as a fraction of D
z_k	Binary variable indicating the selection of a back-up supplier for part k
a_k	Capacity for part k at backup supplier as a fraction of D
v_{kj}	Auxiliary variable to link the primary supplier capacity quantity to the piece-wise linear capacity cost.
l_{kj}	Auxiliary variable to link the secondary supplier capacity quantity to the piece-wise linear capacity cost.
n_{kj}	A binary variable: if $w_j \leqslant \psi_k D x_k \leqslant w_{j+1}$ then $n_{jk} = 1$, otherwise $n_{jk} = 0$.
o_{kj}	A binary variable: if $w_j \leqslant \psi_k D y_k \leqslant w_{j+1}$ then $o_{jk} = 1$, otherwise $o_{jk} = 0$.
Parameters	
f_{kj}	Unit cost of reserving capacity for part k from primary supplier at the break point j.
h_k	Unit cost of holding inventory capacity at primary supplier for part k.
c_k	Fixed cost of selecting secondary supplier for part k (include tooling and contract cost)
q_{kj}	Unit cost of reserving capacity for part k from secondary supplier the break point j.
b_k	Fixed cost of selecting backup supplier for part k
r_k	Unit cost of reserving capacity for part k from backup supplier
m_k	Maximum surplus capacity for part k from primary supplier
g_k	Maximum reserved capacity for part k from secondary supplier
p_k	Maximum reserved capacity for part k from backup supplier
w_j	The capacity on breakpoint j
D	Expected daily demand for final product during the planning horizon
ψ_k	Usage rate of part k in final product

$$\psi_k D y_k \leqslant \sum_{j \in J} w_j l_{kj} \qquad \forall k \in K, \tag{11}$$

$$l_{k1} \leqslant o_{k1} \qquad \forall k \in K, \tag{12}$$

$$l_{kj} \leqslant o_{kj-1} + o_{kj} \qquad \forall k \in K, j \in 2, \ldots J-1, \tag{13}$$

$$l_{kJ} \leqslant o_{kJ-1} \qquad \forall k \in K, \tag{14}$$

$$\sum_{j \in J} l_{kj} = 1 \qquad \forall k \in K, \tag{15}$$

$$\sum_{j \in J} o_{kj} \leqslant 1 \qquad \forall k \in K, \tag{16}$$

$$e_k \leqslant 1 \qquad \forall k \in K, \tag{17}$$

$$z_k \leqslant 1 \qquad \forall k \in K, \tag{18}$$

$$x_k \psi_k D \leqslant m_k \qquad \forall k \in K, \tag{19}$$

$$y_k \psi_k D \leqslant g_k e_k \qquad \forall k \in K, \tag{20}$$

$$a_k \psi_k D \leqslant p_k z_k \qquad \forall k \in K, \tag{21}$$

$$s_k > 0 \qquad \forall k \in K, \tag{22}$$

$$x_k, y_k, a_k \in [0,1]; z_k, e_k, v_{kj}, l_{kj}, n_{kj}, o_{kj} \in \{0,1\}; s_k \in \mathbb{R}^+. \tag{23}$$

The objective function (3) minimizes the total cost consisting of reserve capacity at primary and secondary supplier locations, fixed cost of the signing contract with secondary and back up suppliers, cost of purchasing parts from backup suppliers, and total cost of holding of safety stock at primary supplier location.

Constraint (4) guarantees backup capacity for satisfying demand will be reserved at primary and secondary suppliers. Constraints (5)–(16) are related to piece-wise linear reserving capacity at primary suppliers with unit piece price f_{kj} and secondary suppliers with price q_{kj}. Constraint (17) ensures that at most one secondary supplier is chosen for part k. Similarly, constraint (18) ensures that at most one backup supplier is chosen for the part k. Constraint (19) guarantees that the level of regular capacity reserved at the primary supplier does not exceed the maximum capacity level of the primary supplier. Constraints (20) and (21) ensure that the total amount of reserve capacity from secondary and backup suppliers is not greater than the maximum allowed reserved capacity. Finally, constraints (22) and (23) represent bounds on decision variables.

The mathematical model is used to find the optimal mitigation strategies for a given supply chain network. Then, the values of decision variables will be considered input of discrete event simulation to reassess the resilience with new structures.

4.2. Simulation

In this section, simulation framework is developed to assess resilience of the supply network and verify the performance of mitigation strategies suggested by the mathematical model in the previous section.

4.2.1. Design of experiment

The experiments are a crucial part of the engineering and simulation process because they help decision-makers and managers to understand how the systems and processes work. The validity of simulation outcomes and decisions are dependent on how the experiments are conducted; for this reason, we employ the design of experiment (DOE) method (Longo and Mirabelli, 2008; Kleijnen, 2005). We generated 14 initial samples for decision variables, including primary capacity (x_k), secondary capacity (y_k), backup capacity (z_k), and safety stocks (s_k) for each tier-1 supplier by applying a two-level factorial design. We have chosen the initial samples that satisfy the following conditions:

$$x_k D + y_k D \geqslant \lambda_\alpha \psi_k D, \qquad \forall k \in K. \tag{24}$$

An $\alpha = 0.95$, representing network service level and λ_α is sampled from normal distribution ($\mathbb{N}(0, 1)$). All initial samples are considered for the deep tier supply network. Then the given network is simulated based on regular disruptions and other policy settings. Finally, the resilience is estimated and considered as output for the linear regression model for each initial sample.

4.2.2. Supply network simulation

The automotive industry is a complex dynamic network consisting of diversified bill of materials, various nodes with different roles, and varied connections between nodes such as material, financing, and information flows. This supply chain network is not easily controllable and predictable while facing disruption events due to its high level of complexity. Therefore, automotive supply chain managements are looking to provide an effective decision support system to plan, design, and control the whole network to improve its resilience and efficiency. In the literature (Persson and Araldi, 2009; Windisch et al., 2015), discrete event simulation (DES) is an appropriate method to tackle the complexity and provide the analytical interpretation. Thus, a DES model would be the most appropriate approach for assessing complex networks' resilience when disruption events can halt production. Mainly, decision-makers can include the dynamics and the simplicity of modeling through the supply chain system analysis by employing DES (Agalianos et al., 2020). Ultimately, DES can capture the uncertainty and complexity, and is well-suited for complex supply chain studies. There are several commercial DES software (Solutions, 2019). We used the Simpy (Python package) (Müller and Vignaux, 2002) because it gives us the flexibility to generate different network structures by integrating with the NetworkX package (NetworkX, 2004). The package defines various random disruptions, and design valuable performance indices dashboard using available Pythons features. This study follows the research presented in Taghizadeh et al. (2021) for implementing DES simulation through the supply chain network while considering inventory policies, shipment policies, and demand generation for each supplier located in different tiers. All the results presented for the real case study section are obtained from the DES simulation algorithm using python Packages.

4.3. Surrogate Model

As noted earlier, supply chain resilience management is multidimensional in nature, and decision-makers need to optimize all key performance metrics such as capacity utilization, costs, lead times, service levels, etc. Our resilience management framework establishes a surrogate model in the optimization section by generating linear regression for each tier-1 supplier. Algorithm 1 describes how surrogate model is created and optimization model is updated during resilience management framework.

Algorithm 1. Surrogate Model

1 **Step 1:** Define the initial optimization formulation referring to (3)–(23) and solve the initial model
2 **Step 2:** Run network simulation (see Section 4.2.2) using initial samples and optimal values of decision variables from step 1 to estimate the resilience of each tier-1 supplier (see Section 3.1).
3 **Step 3:** Using simulation results from step 2, generate (or update) a linear relationship between the estimated resilience level and independent variables for each tier-1 supplier (see Section 4.3.1).
4 **Step 4:** Relationships from step 3 form new or updated constraints for the focal firm and each tier-1 supplier. These constraints are added to the optimization model as suggested in (25)–(28) (see Section 4.3.2).
5 **Step 5:** Solve the updated optimization problem and obtain the optimal values of the decision variables.

(continued on next page)

(*continued*)

6 **Step 6:** Run network simulation using the new optimal values of decision variables and estimate the resilience levels.
7 **Step 7: If** $R_F \geqslant \overline{R_F}$, the optimal mitigation strategies for each tier-1 supplier has been finalized. **Else** Move to step 3.

The goal is to maximize focal firm's resilience while considering multi-dimensional aspects such as minimizing cost or delayed deliveries. The details for updating the optimization model are summarized in the following sections.

4.3.1. Linear Regression Model

In the regression model, tier-1 suppliers resilience levels are considered as dependent variables, and the amount of reserve capacity at primary (x_k), secondary (y_k), and backup suppliers (z_k), and safety stock (s_k) are considered as independent variables. To define the surrogate model for our framework, we have $k \in K$ suppliers with different resilience levels (R_k) obtained from simulation step, and a set of independent variables: $X_k = x_k.D.\psi_k, Y_k = y_k.D.\psi_k, Z_k = z_k.D.\psi_k, s_k$. Finally, we generate a linear relationship between resilience levels (Focal Firm and tier -1 suppliers) and other independent variables. The details of linear regression are as follows:

$$R_k = f_{R_k}(X_k, Y_k, Z_k, s_k) = \beta_0 + \beta_1 X_k + \beta_2 Y_k + \beta_3 Z_k + \beta_4 s_k + \epsilon_{R_k} \quad k \in K$$

$$R_F = f_{R_F}(R_1, R_2, \ldots.., R_k) = \gamma_0 + \gamma_1 R_1 + \gamma_2 R_2 + \ldots.. + \gamma_k R_k + \epsilon_{R_F} \quad k \in K$$

4.3.2. Updating Optimization Problem

Most of the dependent and independent variables are continuous, and we have $k+1$ dependent variables. The primary interest is to minimize cost while satisfying R_F and $R_k, k \in K$ to attain the target focal resilience level $\overline{R_F}$ (25).

Min Cost (3)

$$R_F \geqslant \overline{R_F} \tag{25}$$

$$\left| R_F - (\gamma_0 + \gamma_1 R_1 + \gamma_2 R_2 + \ldots.. + \gamma_k R_k) \right| \leqslant \theta \widehat{\sigma}_{\epsilon_{R_F}} \tag{26}$$

$$\left| R_k - (\beta_0 + \beta_1 x_k + \beta_2 y_k + \beta_3 z_k + \beta_4 s_k) \right| \leqslant \theta \widehat{\sigma}_{\epsilon_{R_k}} \qquad \forall k \in K, \tag{27}$$

$$R_F, R_k \in \mathbb{R}^+. \tag{28}$$

The accuracy of the formulation results relies on the quality of regression models. Since the regression models are not guaranteed to be perfect, constraints (26)–(27) have been added to cover the imperfection of regression models. The slack is defined as $\theta * \sigma$, where σ represents the regression model standard error, and a smaller value of θ will create the strict condition; for instance, when θ equals zero, the regression model need to design to predict the independent values but for θ values more than zero, the regression models can have flexibility. Finally, (25)–(28) will be added to optimization model.

5. Results & managerial implications

5.1. Automotive supply network setting

We demonstrate the capability of the proposed deep-tier resilience management framework in a real world case study for an automotive climate control sub-system. For this purpose, a tier-3 supply chain network belonging to a global automotive original equipment manufacturer (OEM) located in North America has been evaluated. The network consists of different suppliers located in various locations with different regional risk indexes (for details, refer to Table 2). In Table 2, regional risk indexes are obtained from the IHS Markit website

Table 2
Location with IHS Markit's unique country risk. (Source: IHS Markit 2020; Updated Q2-2020).

Suppliers ID	Location	Risk Index
Final Assembly Plant, $S_{11}, S_{12}, S_{14}, S_{15}, S_{16}, S_{17}, S_{21}, S_{22}, S_{27}$	MX	2.7
$S_{13}, S_{23}, S_{24}, S_{28}, S_{32}$	USA	1.6
S_{25}	FR	1.7
S_{26}	KR	1.5
S_{31}	BR	2.5

FR: France, KR: South Korea, MX: Mexico, BR: Brazil.

(IHSMARKIT, 2020) which is a distinguished secondary database. The final assembly plant's daily production volume follows the normal distribution $\mathcal{N}(\mu = 410, \sigma^2 = 100)$, and the (s,S) inventory policy has been considered for all tier-1, -2, and-3 suppliers and final assembly plants. (see Table 3).

In Fig. 2 shipping information including shipping mode, duration, and frequency between suppliers in different tiers and between tier-1 suppliers and the final assembly plant is shown. For instance, between suppliers S_{26} and S_{17}, there are two types of shipping modes with three different settings. First, it has road shipping which happens every three weeks, and each delivery takes one day; then it switches to sea shipping, which happens every two months with a seven-week delivery duration; finally, there is a road shipping happening every three weeks with a one day shipping duration. Part names for each supplier are shown in Fig. 2; for instance, suppliers S_{15} and S_{23} shipped A/C Ducts and Motors to the final assembly plant and supplier S_{11}, respectively. Lead time and other supply network settings such as holding cost, backordered cost, initial inventory, safety stock, and shipment capacity follow the same settings suggested in the study by Taghizadeh et al. (2021).

All key performance metrics such as lost demand, costs, lead times, service levels, and capacity utilization have been tracked in this case study. In addition, the lost demand has been considered as a key performance function to assess the resilience of the focal firm and all suppliers during the simulation.

Table 3
Comparison proposed framework with different slack values for generate regression function under target level 97.5%.

	θ=2	θ=0	θ=1	θ=3
R^2	0.77	0.86	0.81	0.69
Focal Firm (R_F)	97.56	97.5	97.54	97.8
S_{11} (R_1)	97.62	97.58	97.63	97.85
S_{12} (R_2)	98.03	97.63	97.96	98.31
S_{13} (R_3)	98.23	97.57	97.92	98.46
S_{14} (R_4)	97.98	97.61	97.83	98.19
S_{15} (R_5)	98.02	97.93	98.01	98.16
S_{16} (R_6)	97.61	97.65	97.63	97.88
S_{17} (R_7)	97.78	97.53	97.74	98.09
Holding Cost (Per Year)	$28,071	$27,018	$27,950	$29,837
Backordered Cost (Per Year)	$9,012	$9,901	$9,175	$8,579
Primary Capacity Cost (Per Year)	$418,004	$408,016	$417,094	$421,133
Secondary Capacity Cost (Per Year)	$175,632	$175,448	$175,514	$184,189
Inventory Level (Per Month)	1115	1116	1127	1186
Max Inventory Level (Per Month)	2159	2161	2164	2205
Min Inventory Level (Per Month)	0	0	0	0

R^2:R squared for regression model with dependent variable is Focal Firm Resilience Level (R_F).
R: Resilience Level Eqs. 1,2.

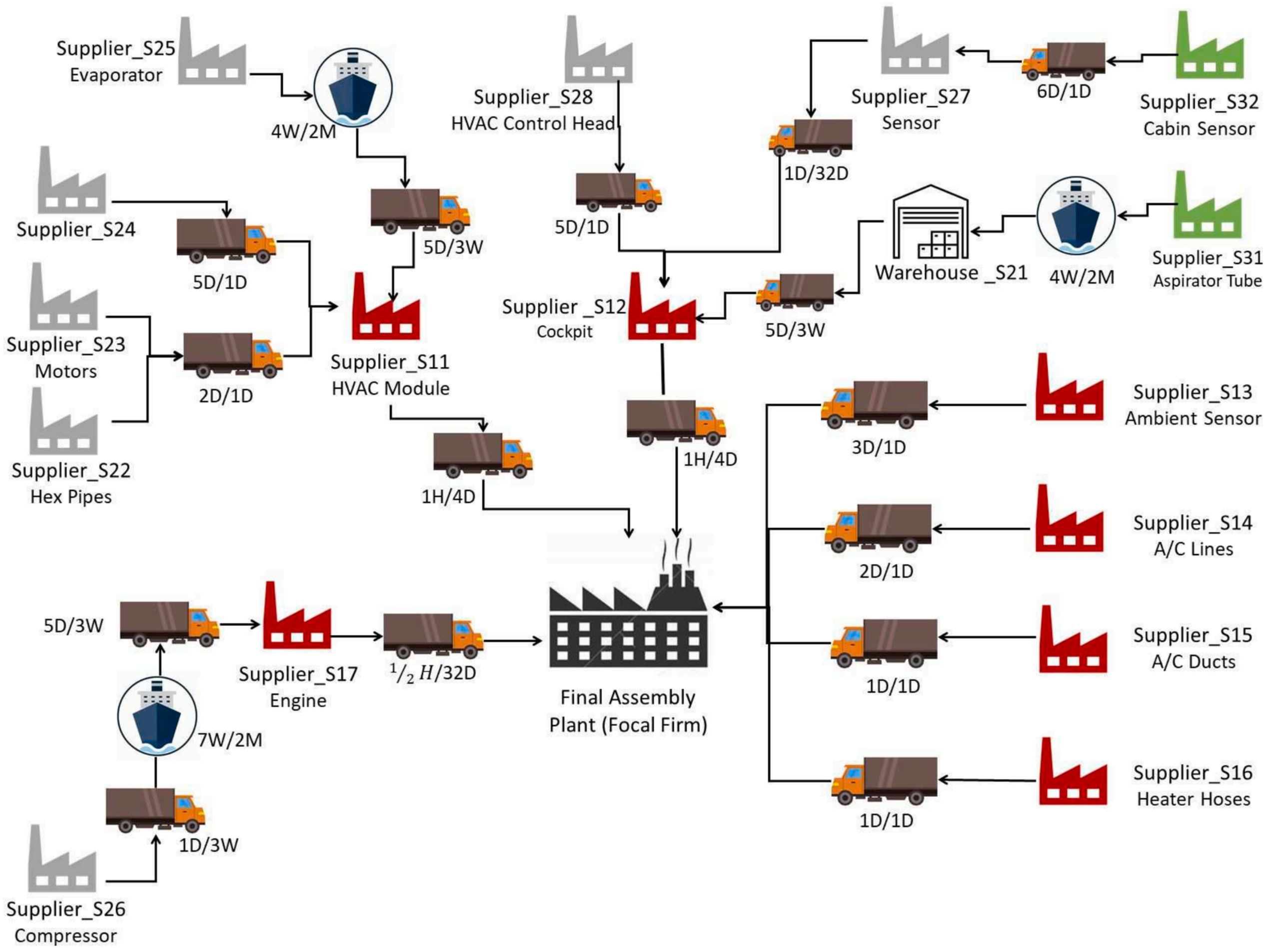

Fig. 2. Case study supply network for an automotive climate control system. H: hours, D: days, W: weeks, M: months.

5.2. Simulation settings

As noted in Section 4.2.2, DES has been chosen as the well-suited method to assess network resilience. Once the optimal strategies and capacity levels of primary, secondary, and back suppliers are obtained under given scenarios, the deep-tier supply network is simulated for $T =$ 1,095 days with a warm-up of 90 days and 10 replications. During the simulation, regular disruption frequency and intensity are estimated according to the regional risk index (for details, refer Taghizadeh et al. (2021)), and all expected performance metrics and resilience levels (Section 3.1) for final assembly plant and tier -1 suppliers are measured. The following visibility scenarios are defined and considered for simulating the defined case study to evaluate the effectiveness of the proposed resilience management framework in the deep-tier supply network.

- **Full Visibility**(SC0): Visibility to all major tiers of the supply network. Further upstream suppliers are assumed to be perfectly reliable and do not experience disruptions.
- **Typical Scenario** (SC1): Network visibility limited to tier-1 suppliers.

A personal computer with the Intel Core i5-6300U CPU (2.4 GHz) and 8.00 GB RAM has been used for running the proposed simulation-based optimization. In the following subsections, we discuss the results of employing the proposed framework to reach the given target resilience levels under different levels of visibility with a brief discussion of significant managerial insights obtained from our study.

5.3. Optimal resilience strategies for deep-tier supply network

This section provides details of computational experiments across simulation replications under the different scenarios (i.e., different levels of deep-tier visibility) for three focal firm target resilience levels (95%, 97.5%, and 99%).

Fig. 3 compares two levels of visibility under three different target resilience levels. The results confirm an overestimated resilience when the network is limited to tier-1 suppliers for all defined scenarios.. Moreover, the resilience overestimation is very tangible in Fig. 3.a when decision-makers do not set any target resilience and not consider any mitigation strategies. Our resilience management framework can reduce this gap. However, the overestimation of resilience cannot be ignored, and Fig. 3.b demonstrates the importance of considering additional information and deep-tier visibility to achieve the expected resilience of all tier-1 suppliers and focal firms. In addition, Fig. 3.b compares the resilience levels tier-1 suppliers and focal firms when the focal firm's resilience target level has been set as 95% and 99%. The results illustrate that for the 99% resilience level, supply chain managers need to define optimal mitigation strategies that can keep most of the tier-1 suppliers in the 99% resilience level. However, there is not the high tightness for tier 1 suppliers in 95% scenarios. For instance, in the 99% target resilience, almost five of seven tier-1 suppliers have posed the 99% resilience level in comparison 95% scenarios in which just three tier-1 suppliers need to meet the maximum resilience. Finally, it can be concluded that our effective resilience management framework demonstrates consistent performance in different visibility scenarios and how the optimal mitigation strategies can cover all tier-1 suppliers' vulnerabilities to reach an acceptable level.

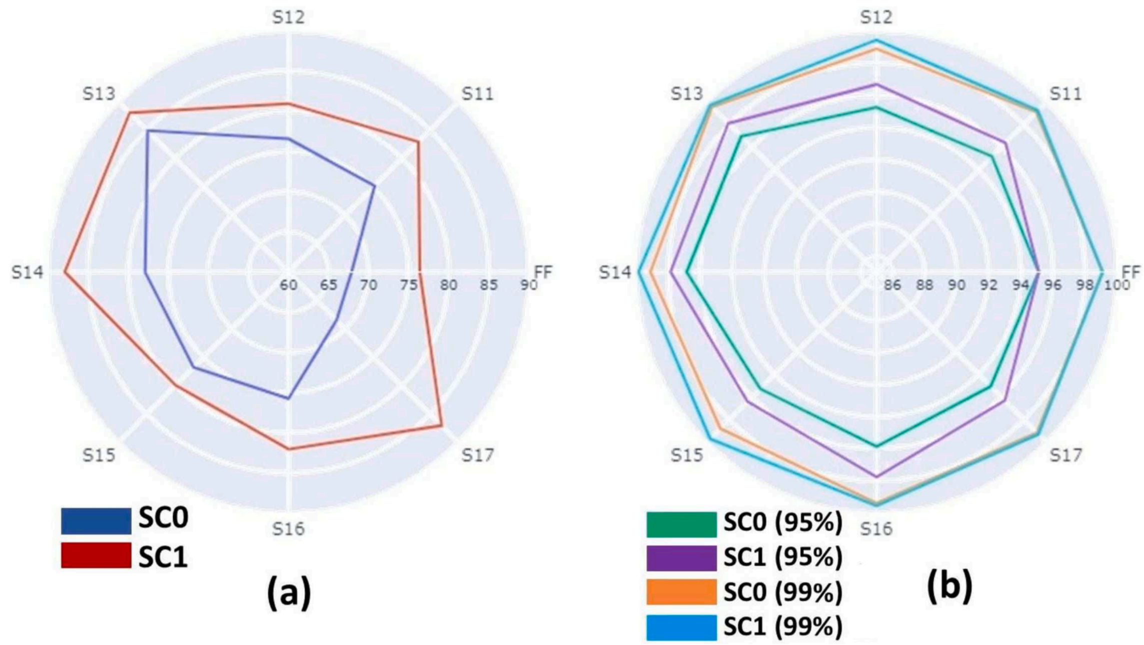

Fig. 3. Estimated node resilience for focal firm (FF) and tier-1 suppliers under different levels of upstream visibility and different resilience target level [Full Visibility Scenario (SC0), Typical Scenario (SC1)].

Fig. 4 reports the level of reserved capacity at primary and secondary suppliers for all tier-1 suppliers in our case study under different visibility scenarios and target resilience levels. The results present more reserved capacity at primary suppliers when the supply chain network has limited visibility (SC1). However, in another scenario involving visibility and transparency beyond tier-1 suppliers, the resilience management framework suggests more reserved capacity at the secondary suppliers' location to reach the expected resilience level. Fig. 4 highlights that when the supply chain network is looking for a higher resilience level, the optimal mitigation strategy offers more reserved capacity levels at primary suppliers in comparison to secondary suppliers, which can be because of considering the trade-off between cost and resilience level. In the following section, other key performance indexes (KPIs) under different target levels will be discussed to find out how the proposed framework can be effective and efficient.

5.4. Supply cost and responsiveness assessment

Fig. 5 plots the holding and backordered costs under three mitigation scenarios: no mitigation strategies; considering the 95% target resilience

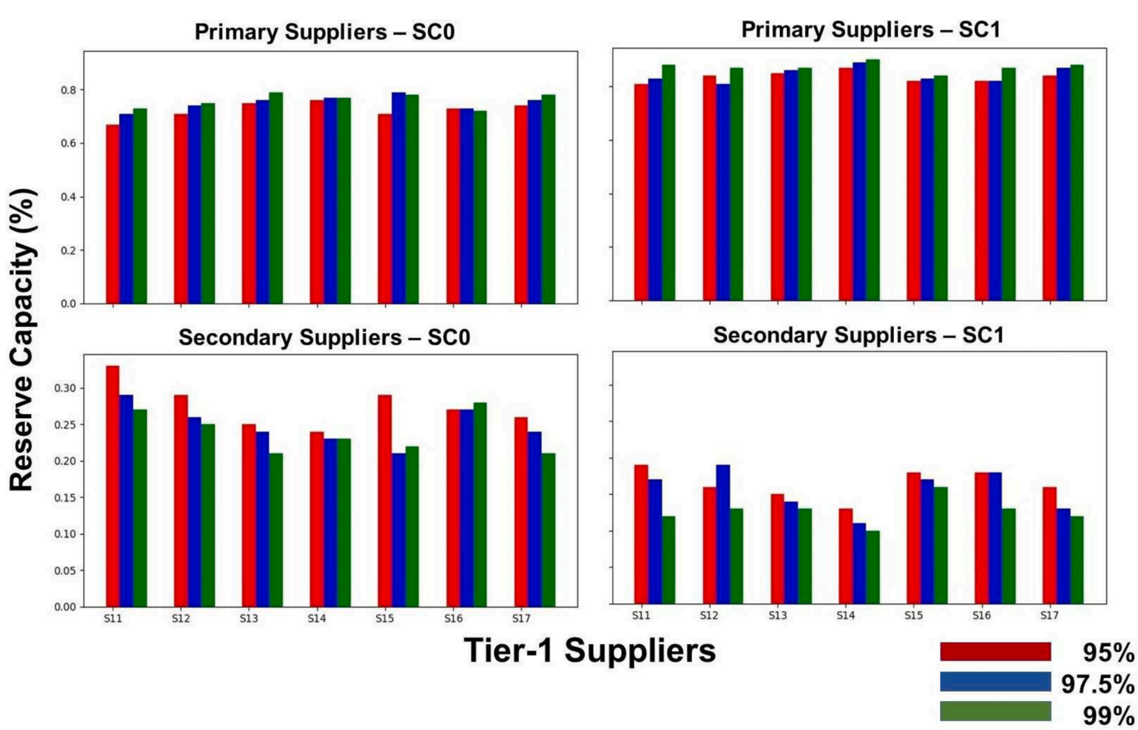

Fig. 4. Optimal reserve capacity level at primary and backup suppliers for different resilience target level [Full Visibility Scenario (SC0), Typical Scenario (SC1).

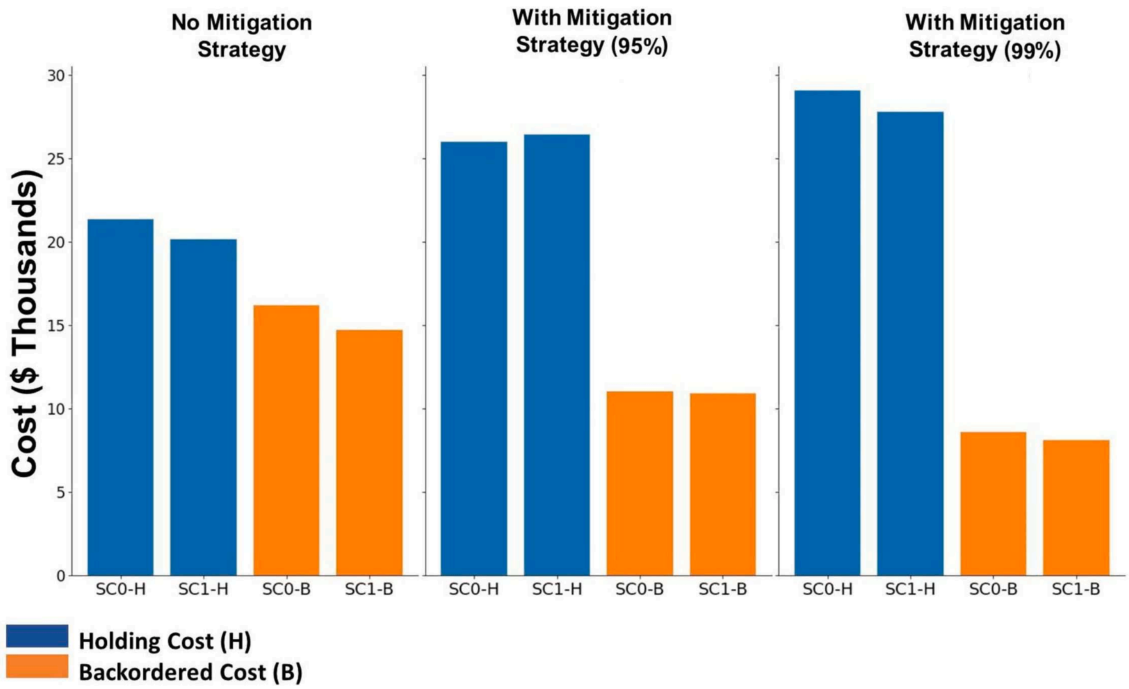

Fig. 5. Estimated total holding and back-ordered cost for focal firm under different levels of deep-tier visibility and target resilience level [Full Visibility Scenario (SC0), Typical Scenario (SC1)].

level; and considering the 99% target resilience level. For the length of simulation (around three years), the resilience management framework can improve the backordered cost and reach expected resilience at the focal firm by experiencing a gentle and negligible increase in holding cost. By implementing the proposed resilience framework, we significantly reduce backordered costs. For instance, during our network simulation, we see an average 33% and 41% reductions when the supply network moves from no mitigation strategies to considering 95% and 99% targeted resilience levels, respectively. In addition, we can see the same and consistent behavior under different visibility scenarios, which can prove that the proposed framework is efficient.

As noted earlier, resilience is multi-dimensions, and shipment delays or lead-time delivery is one of the critical performance metrics that has been considered in this research. Fig. 6 reports the distribution of order shipment delays of tier-1 suppliers under two categories (without mitigation strategies and with mitigation strategies for 99% target resilience

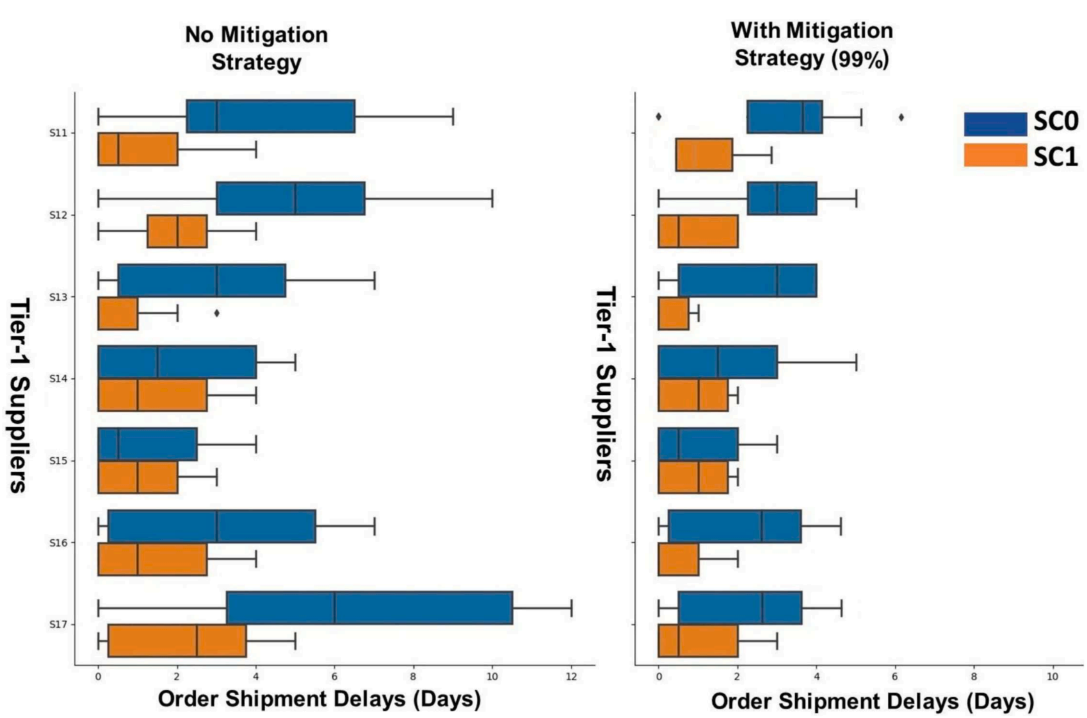

Fig. 6. Estimated order shipment delays by tier-1 suppliers under two different visibility scenarios and mitigation strategies [Full Visibility Scenario (SC0), Typical Scenario (SC1)].

level) with different visibility levels. For instance, when the supply network does not consider any mitigation strategies, supplier S_{11} shows the maximum 9 and 4 days delivery to focal firms under full (SC0) and limited (SC1) visibility scenarios, respectively. On the other hand, when proposed resilience management optimizes the mitigation strategies to reach the 99% resilience level, the supplier S_{11} poses the maximum 4 and 3 days delivery delays under two deep and typical visibility scenarios. The results show that the proposed framework can lead to a more reliable delivery time with minimum shipment delays than the network without affordable strategies.

5.5. Optimal resilience strategies for different slacks setting

Table 5.5 reports detailed results under various slack values when the supply chain network poses full visibility with a 97.5% target resilience level, as noted in Section 4.3.1 regarding adding slack (*theta*) to cover the imperfection of regression models. The estimated tier-1 suppliers' resilience levels, holding and backordered costs, primary and secondary reserved capacity levels, and inventory levels have been compared, and they demonstrate more tightened behavior for the supply chain network when θ=0 (minimum values). For example, when θ=0, the costs and variance of a supplier's resilience level are lower than when θ=2 or 3. Furthermore, the results demonstrate the consistency of behavior under different simulation settings (θ=0,1,2, and 3), with only a negligible increase in costs and inventory levels when θ's value is changed from 0 to 1,2, and 3.

5.6. Managerial implications

The findings of this study provide significant managerial insights for enhancing supply chain resilience. The proposed dynamic framework offers a proactive approach to designing and managing resilient supply networks, particularly in the automotive industry. By integrating simulation-based resilience assessment with an optimization-based framework, managers can achieve desired resilience levels while minimizing costs and maximizing operational efficiency. The framework's ability to analyze deep-tier supply chains allows for more precise identification of vulnerabilities and risk mitigation strategies. To effectively implement this framework, managers must first understand their tiered supplier structures and identify all potential risks. By applying this framework, they can optimize their mitigation strategies across various scenarios, leading to substantial reductions in back-ordered costs and shipment delays. This approach not only improves decision-making processes but also ensures that resilience strategies are well-aligned with the complex, multi-dimensional nature of modern supply chains.

6. Conclusion

Supply chain networks must be designed or redesigned to be more resilient in the face of an uncertain environment with more frequent or severe disruptions. As with many other industries, the automotive industry relies upon complex and vulnerable supply chain networks due to globalization and lack transparency beyond immediate suppliers. Developing an efficient and practical network resilience management to optimize the mitigation strategies while considering assumptions such as mapping deep-tier networks, real-time inventory policies, and related shipment policies is vital for decision-makers. The current study was designed to propose a dynamic resilience management framework that is informed with secondary data sources to optimize the mitigation strategies of a deep-tier supply chain network. The dynamic framework has been tested with a real-world and complex automotive supply chain network. The mitigation strategies have been evaluated with regular disruption scenarios to understand which tier-1 suppliers will be fragile and vulnerable in the face of disruptions. The framework and its scenarios reflect the real risk that OEMs and others can face, and the results illustrate the importance of considering regional risk and deep-tier visibility. This framework allows decision-makers to choose the best strategies that better fit their network structure and risk profiles.

In this framework, feasible mitigation strategies such as reserving capacity at primary and secondary supplier locations, contracting with backup suppliers, and holding more initial inventory have been considered. Due to the multi-dimensional nature of the supply chain resilience, the optimal mitigation strategies for given disruptions have been chosen by reviewing the different performance indexes such as cost, capacity utilization, lead time, and delay delivery. The results demonstrate that relying on primary and secondary capacities while facing random and low severity disruptions; and relying on the backup capacity for critical suppliers in long disruption scenarios. In addition, the results verify the impact of ignoring deep-tier visibility on the total cost when facing severe disruption. However, providing the proper mitigation strategies by considering a high level of visibility can alleviate the consequences of extreme disruptions.

The proposed methodology provides an adaptable framework for other industries as well. One potential future research extension includes studying the effect of supply chain structures of other industries on the proposed resilience management framework. Additionally, Blockchain technology can enhance resilience by offering a decentralized, tamper-resistant ledger that ensures data integrity and security, thereby reducing single points of failure and bolstering the system's defense against attacks and disruptions. Future studies could investigate the integration of AI or Blockchain technologies to further advance resilient supply chain solutions. By applying sensitivity analysis to key parameters, such as the resilience of the focal firm in response to uncertainties in regional risk indices, inventory holding costs, capacity expansion costs, and other industry-specific factors, the robustness of the resilience framework can be evaluated under various scenarios. Another avenue is to improve the efficiency of the proposed resilience management methodology by improving the accuracy of the surrogate model in the simulation-based optimization framework. This can be done by incorporating supply network structure parameters into the regression model or by incorporating nonlinear regression functions. Finally, future research can explore risk-averse formulations for resilience management.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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