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Framework For Effective Resilience Managmenet Of Complex Supply Networks

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**FRAMEWORK FOR EFFECTIVE RESILIENCE MANAGMENT OF
COMPLEX SUPPLY NETWORKS**

by

ELHAM TAGHIZADEH

DISSERTATION

Submitted to the Graduate School

of Wayne State University,

Detroit, Michigan

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Approved By:

Advisor

Date

Co-Advisor

DEDICATION

I dedicate my dissertation work to my family and friends. A special feeling of gratitude to my loving husband, Babak, for his encouragement, endless love, and support.

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CHAPTER 1 INTRODUCTION

The effectiveness of a supply chain network can be judged by tracking how well it keeps costs to a minimum while guaranteeing service and drives up efficiency over time. Just-in-Time (JIT) practices enabled by modern information and communication technology allowed the supply chain profession over the past several decades to reach higher levels of operational excellence by allowing facilities to build and deliver goods to customers at the expected time, while minimizing waste and inventory holding costs. However, globalization of production/distribution networks and single sourcing practices combined with increasing risks from natural disasters (e.g., due to global warming and pandemics) and man made events (e.g., labor strikes, accidents) are creating a so called ‘new normal’ environment where unexpected events and disruptions have become too routine and the norm.

In 2011, a massive and fatal earthquake and tsunami in Japan halted factories and several assembly plants that provided critical electronic parts for the automotive industry [19]. In 2018, Ford Motor Company suspended the F-150 truck production line, their most profitable product, for seven days due to a massive fire at a supplier plant, and spent millions to return to normal [54]. The ongoing COVID-19 pandemic has delivered massive shocks to supply chains across all industries around the world. Even after more than 20 months into the pandemic, the consequences are quite severe. The 2020–21 global ‘chip’ shortage is an ongoing crisis in which the demand for integrated circuits (commonly known as semiconductor chips) is greater than the supply, affecting numerous industries including the automotive industry, and forcing plant closures, lower levels of production, and even product redesign to mitigate the impact [55]. According to Wikipedia, the cause

of the chip crisis is a combination of different events with the snowball effect of the COVID-19 pandemic being one reason and other causes attributed to the China–U.S. trade war and the 2021 drought in Taiwan. Going forward, according to a recent McKinsey Consulting report, companies across industries can expect supply chain disruptions for a month or longer every 3.7 years; it means the most severe events are happening more frequently [78]. This is leading to unintended consequences for JIT strategies because the supply chain ecosystem is not designed and managed to react effectively to disruptions and recover quickly to its normal operation status.

All this suggests that the supply chain management practice needs to consider features such as growing supply network complexity, various types of risks/disruptions, and improve visibility throughout the network. Researchers and industry analysts are looking to develop more practical and effective resilience strategies that are compatible with current-day supply networks.

Resilience was first introduced as a descriptive ecological term by Holling’s study on ecosystems in 1973. The author defined ‘resilience’ as the property of ecological systems responsible for keeping the ecosystem in a regular manner when it faces changes in system variables or parameters [51]. In the last 40 years, resilience has expanded in various ways from psychology to supply network management [72]. Most supply network research provides several definitions of resilience to propose a practical framework for resilience in the supply network by optimizing given objective functions. In most research, network resilience has been considered as an inherent ability of a network that can restore the network’s operation to a stable or normal level when any disruption (expected or unexpected) occurs [13, 22, 53]. Other studies consider resilience as the ability of the

system to recover from external and internal disruption events and reach acceptable or optimal operational or service levels [17, 36, 124]. Overall, a supply chain network can be deemed reliable and resilient when preventing, adapting, and recovering from disruption events. Therefore, supply chain managers need to first assess resilience to investigate if the resilience level needs to be improved by implementing appropriate resilience management strategies.

Different quantitative and qualitative approaches have been introduced to assess the resilience of the supply chain network in the literature. For instance, design surveys to find network resilience is a type of qualitative aspect. Research in 2013 proposed a survey to understand how firms and organizations within various industries can handle and get rid of disruption events such as loss of suppliers or shipping delays to keep their operation at an acceptable level in competitive markets [40]. Other studies designed a survey to define and review factors that can improve supply chain resilience [73, 121]. Furthermore, most qualitative studies can help decision-makers list factors with a high-rank impact on supply chain resilience. In addition, quantitative methods exist to measure the resilience score or levels [65]. The quantitative methods define various performance indexes such as service level, demand coverage, capacity level, shipment delay, and recovery duration to develop a quantitative measurement [31, 38, 50, 53, 111]. Recently, a new point of view has been added to assess the resilience of supply chain network, considering network ‘structures’, and integrating qualitative and quantitative methods with social network analysis.

Most research studies in resilience assessment that consider social network analysis rely on static ‘network analysis’ techniques and metrics such as ‘centrality’ and ‘density’ to measure and evaluate the performance of a supply chain network [67, 82, 114, 117, 134,

135]. This type of analysis and view in resilience assessment can propose some interesting insights at a macro level. For instance, R. C. Basole [10] discuss how the role of network structure can be effective in supply chain risk assessment and verify the value of deep-tier visibility in risk mitigation for the electronics industry. Another study demonstrates the relationship between network structure and a firm's performance in a non-related supply chain context in several industries while considering a number of control variables such as firm size [11]. However, such static analyses, without considering supply chain operation indexes, are generally not adequate for providing actionable guidance to individual firms in managing the resilience of supply networks for individual products or commodities [20, 30]. For example, warehouses would by their very purpose maintain high in- and out-degree centrality, and assemblers would maintain higher in-degree centrality due to their various roles within supply networks. The network structure can also vary based on facility locations and regions.

There is a gap in the literature regarding comprehensive resilience assessment methodology to cover all complexities and features in the supply network. A resilience assessment framework should account for supply chain characteristics such as network structure, inventory policies, logistics, demand variability, and most importantly, the reliability of the operations and activities across the supply network. The methodology should also account for different disruption possibilities and expected recovery profiles. Finally, the framework needs to consider the multi-dimensional nature of supply chain resilience and evaluate all potential performance indexes. To the best of our knowledge, no quantitative study in the supply chain resilience domain have adequately addressed resilience assessment accuracy and the need for increasing deep-tier transparency. This study over-

comes this research gap by proposing a comprehensive multi-dimensional framework to evaluate supply network resilience.

Research studies and industry practices verify that organizations can be more reliable and resilient against the various disruptions by adopting optimal mitigation strategies such as dual sourcing, increasing inventory levels, and maintaining surplus capacity. To achieve optimal mitigation strategies, quantitative modeling, simulation, and optimization techniques are needed [26]. Various approaches and methodologies have been introduced, including system dynamics [129], stochastic optimization [39, 92], agent-based simulation [85], scenario approach [94], nonlinear programming model [95], game theory [89], and network theory [44]. These methods have offered recovery or mitigation strategies by optimizing and tracking various performance metrics. However, no studies consider the deep-tier visibility with all forms of complexity typical to supply chain networks to optimize the resilience. As we noted earlier, most disruptions come from tier-2, tier-3 suppliers, and according to real industry practices, supply chain managers must consider maximum transparency and visibility to design optimal strategies.

This research study employs simulation-based optimization for resilience management because digital simulation models of supply networks can provide adequate accuracy for modeling uncertainty and disruption scenarios [119]. The related objective function can be minimizing cost of doing business or shipment delays or maximizing service level (or a combination) and need to be optimized based on digital simulation model output. Another advantage of this method is assessing resilience levels through the supply network to ensure that we have proper strategies for the given network. This research study uses the automotive industry as a real case study to evaluate our resilience assistance and

management framework when exposed to operational (frequent) disruptions. The main mitigation strategies are reserved capacity at primary and secondary suppliers or contracts with back suppliers for reserving extra capacity. These strategies are acceptable for automotive industries, and without loss of generality, we consider cost as an objective function that needs to be minimized.

1.1 Research Objectives

The primary objective of this research is to develop a practical and effective resilience assessment and management framework for supply networks with different ranges of complexity (tiers, nodes, edges, scale, and structure). The framework should account for supply chain parameters (e.g., inventory policies, logistics, and demand variability), network structure, and disruption scenarios (e.g., severity, frequency, duration, and recovery profiles). The overall research objectives can be summarized as follows:

1. ***Resilience Assessment***: A resilience assessment framework should be developed to meet the following objectives:

- Improve the fidelity of supply network resilience assessment methods by mapping deep-tier networks and using secondary data sources to extend network visibility. The framework should characterize the role of supplementary information in improving network resilience assessment for generalizable insights.
- The framework should integrate social network analysis, supply chain parameters, and discrete-event simulation for improving assessment accuracy. Analysis of variance techniques should be employed for identifying significant generalizable factors that most influence network resilience.

- The framework should establish a mechanism for identifying critical nodes, arcs, and regions of the network that most impact supply network resilience.
- The resilience assessment framework should support different types of supply networks, representative of various automotive commodities and their diverse structures and complexities.
- The framework is to be validated using several case studies and secondary databases considering regional risks.

2. **Resilience Management:** Here the objective is to develop a robust decision support framework to optimize the resilience during network reconfiguration and design. Resilience management will employ efficient simulation-based optimization techniques while considering the strategic allocation/distribution of safety buffers (e.g., capacity, inventory, dual-sourcing) across the network (e.g., supplier selection, location, mode of transportation). Proposed method should also allow sensitivity analysis and effectively manage disruption scenario planning.

1.2 Research Scope

In this study, we will particularly focus on studying deep-tier automotive supply networks which due to their sheer scale, complexity, and heterogeneity, can lead to very different network dynamics/resilience in comparison with simpler supply networks from other industries. The goal is to develop an efficient framework that can assess and improve network resilience. Specifically, in this proposal, we will focus on mapping the upstream deep-tiers of the supply network (e.g., suppliers of suppliers of direct tier-1 suppliers) and assembly plants for few representative commodities. Considering that this work cannot

be done without a sufficient understanding of a distinct actual automotive supply network and the operations performed within that network, the proposed research will be carried out in the context of real-world case studies. Network resilience being a multi-dimensional concept, a comprehensive and representative set of metrics will be tracked, including inventory and back-order levels, order lead-times, and lost-production, to name a few metrics.

The remainder of the dissertation is organized as follows: Chapter 2 describes the proposed resilience assessment framework informed by secondary data sources, Chapter 3 provides an effective resilience management framework to optimize the mitigation strategies for supply chain network with deep tier visibility, and Chapter 4 offers summary and conclusion of this dissertation and proposes the future research directions.

CHAPTER 2 RESILIENCE ASSASSMENT FRAMEWORK

2.1 Introduction

Operations in modern supply networks have become increasingly intricate and entail complex interactions between customers, retailers, suppliers, and manufacturers. In recent decades, a growing number of organizations have been affected by unforeseen supply network vulnerabilities and disruptions, in industries ranging from pharmaceuticals and consumer goods to electronics and automotive. At the heart of these crises is a common theme the lack of robust processes to identify and successfully manage growing supply network risks as the world becomes more interconnected [107].

Globalization due to emerging markets and efficiencies that stem from low-cost sources has further exacerbated the challenge of supply network risk management. This increased complexity has brought with it more potential failure points and higher levels of risk. According to McKinsey Consulting, the progress in addressing these risks has been slow. Their 2010 survey of 639 executives covering a range of regions and industries, revealed that 71 percent feel that their companies were more at risk from supply network disruption than previously and 72 percent expected those risks to continue to rise [107]. The current COVID-19 situation and the resulting struggles for managing steady supply for even the simplest healthcare supplies creates a stark example of the urgent need for a uniform and proven methodology for assessing and monitoring risks in a way that truly minimizes business disruption due to man-made or natural disasters, the focus of this dissertation.

The suppliers themselves as well as the different actors within the supply logistics

network (from transporters to warehouses and ports) present their own vulnerabilities and risks to downstream players. New regulations, geographical locations and the associated risks (e.g., hurricanes or earthquakes), and geopolitical factors are other sources of disruptions which fall outside the realm of manufacturers and the core supply network [104]. For instance, with thousands of suppliers around the world, the re-negotiation of NAFTA in North America and Brexit has caused massive concerns for automakers. Regulations can be changed overnight, but automakers are unable to react quickly and need time to respond by defining new strategies. [104]. The consequences of supply-chain disruptions can take many forms, including halted production lines, delayed deliveries, unmet demand, lost revenues, and loss of brand reputation and market share. When it comes to the automotive industry, the supply networks are extremely global with deep-tiers, presenting even further challenges in terms of scope and scale of risks as well as visibility for the deep-tiers.

When it comes to the automotive industry, the target industry of this dissertation, the supply network resilience assessment by Original Equipment Manufacturers (OEMs) is generally limited to just the tier-1 (immediate) suppliers with no real consideration for the deep-tiers of the supply network (e.g., suppliers of suppliers of direct tier-1 suppliers). They are no exception in lacking visibility into their upstream tiers. Yet, it is established that this limited visibility results in additional vulnerabilities and could impose massive costs in the tens of millions of dollars [30]. In addition, it is reported that half of all supply chain disruptions typically stem from problems at tier-2 and tier-3 suppliers [6]. The lack of visibility into deep-tier suppliers is often attributed to confidentiality issues or apparent cost. However, our own research reveals that a lack of visibility into the deep-tiers of

the network can significantly distort the accuracy of supply network resilience assessment and a false sense of security. Therefore, seeing beneath the surface and mapping tier-N supplier relationships can enrich the supply network performance by allowing appropriate risk mitigation actions [20, 30].

A common approach to expand supply network visibility is to request information from tier-1 suppliers regarding their suppliers and so on, but this methodology has been proven to be not so practical [29]. Public databases like Bloomberg [15], Marklines [83], and IHS Markit [57] provide some vital information, in particular, for select regions of the world. Other approaches entail using machine learning methods [128] to extract supply network maps from the news [27, 29]. Besides lack of visibility into upstream suppliers, another problematic practice (at least in the academic literature) is the reliance on simplistic supply network analysis techniques for characterizing the resilience of the automotive supply networks [67, 135]. Nodes (firms, facilities, suppliers) can vary in in-degree and out-degree centrality simply because of their roles (e.g., ports) and are not adequate for identifying sources of risk. In addition, network structure/logistics can vary based on facility locations/regions. Most of the extant literature compares basic network metrics such as centrality and shortest path to characterize the resilience level for different network structures (scale-free, random, etc.) [67, 82, 134]. However, sheer scale, complexity, and heterogeneity across the automotive supply networks can lead to very different dynamics/resilience in comparison with supply networks from other industries.

The vast majority of the literature employs qualitative metrics to assess network resilience, using terms such as agility, visibility, flexibility, collaboration, and information sharing [53]. Literature reveals that supply network resilience can be quantified

by defining objective metrics and introducing a dynamic system performance function [135]. A practical resilience assessment and management framework would stem from informed strategic allocation/distribution of safety buffers (e.g., capacity, inventory, and dual-sourcing) across the network (e.g., supplier selection, location, and transportation mode) and not by applying a simple/static set of rules independently for all nodes or arcs. In the following chapter, the proposed resilience assessment framework informed by secondary data sources for a deep-tier supply chain network has been introduced and evaluated by a real case study.

2.2 Literature Review

2.2.1 Visual and Network Analysis of Supply Networks

Recently, there has been a growing recognition of significant benefits of adopting network analytics in the supply chain since the traditional linear supply chains are being replaced by complex and dyadic networks. Rahul C. Basole [8] visualized the fast-moving electronic industries network in three time-steps with their inter-firm collaboration to compare their topological characteristics with their performance level. This study demonstrated that the companies with high performance levels like Apple and Dell have complex collaboration networks with a power-law shaped degree distribution. It suggests that a combination of visualization, network metrics, and performance analysis can help a supply network to highlight the critical nodes and edges and also map inventory, information, and risk flows.

Kim et al. [68] examined the structure of six automotive networks (Accord, Acura, and Grand Cherokee) with two types of connections between nodes (material and financial

flows) while considering social network concepts. The authors utilized the role of social network analysis to qualitatively improve the network performance. For instance, the authors highlighted which firm is critical and which strategy can be appropriate to enrich the performance level of a specific network with known characteristics. Basole and Belamy [10] described how visualization and network analysis could help decision-makers to assess and mitigate risk in electronic industries. They provided a visual supply network dashboard to facilitate risk assessment tasks through each firm (internal risk) and network (external risk) level by investigating network metrics (betweenness and degree centrality). Other studies show the role of social network analysis and visualization to map potential risks of a supply chain network. The authors [93] mapped three different product platforms with material and contractual as connection types. They explored network indicators like product complexity, producer diversity, supply chain length, and potential bottlenecks to assess each network, and finally, they discussed how risks can be recognized and managed by combination of social network and scenario analysis.

An increasing number of studies that employ social network tools to model [12], analyze [11, 14, 69], assess risk [90], and design network [67, 82] show a new stream in supply network analysis.

2.2.2 Supply Network Resilience Assessment

In today's turbulent environment, the supply chain system can face disruptions or unpredictable events. Hence, supply chain strategies to withstand disruption, as well as efficient recovery plans with minimal costs, are critical keys for the entire system [72]. The supply chain resilience literature provides various definitions for resilience, and we summarize them in this section.

The research defines supply chain resilience as ‘the ability of a system to return to its original state or new and more desirable state after being disturbed ’ [22]. Low probability and high impact risks have been considered in supply chain resilience management while high probability with low impact has been addressed in risk management concepts. Another definition is ‘a firm’s ability to absorb disruptions or enable the supply chain network to return to normal state’ [109]. Further definitions include the following: ability of the supply chain to proactively plan and design the network while anticipating unexpected disruptive events, and responding adaptively to disruptions while maintaining control over the structure, and transcending to a robust state of operations [101]; and ‘a network-level attribute to withstand disruptions that may be triggered at the node or arc level’ [67]. All these definitions point to the following key parameters to describe supply chain resilience: predicting unforeseen disruptive events, coping with their consequences, creating an appropriate structure for responding quickly, defining an effective strategy for recovering from disruptions, and returning to a steady or more desirable state [53].

In the following section, the extant literature in resilience metrics and assessment methodologies is reviewed. Most papers provide qualitative metrics with a few quantitative measures introduced for network resilience assessment. One early study of resilience improvement is by Priya et al [102] which focused on production and distribution with demand variability by providing an agent-based framework. A new dynamic and time-dependent qualitative network resilience metric is illustrated by Henry and Marquez [49]. Most prevalent resilience metrics to characterize supply chain networks are service level [102], costs [124], delay delivery, and demand ratio (fill rate) [123]. Some researchers have addressed the resilience assessment problem by exploring network topol-

ogy and social network metrics. For instance, Kim et al. [68] demonstrated how understanding network density, complexity, and discovering the critical nodes can affect supply chain performance. The literature states that the combination of social network concepts with traditional supply network performance measurement is unique and affords more practical applications to supply chain.

2.2.3 Simulation for Supply Network Resilience Assessment

Simulation has been considered as a powerful tool in supply chain resilience and risk analysis [19, 59, 81, 96] due to its well established structure to describe and explore the operation management field. Discrete event simulation is a practical technique to evaluate the supply chain operational performance during and after a disruption. In resilience assessment studies, researchers face challenges in accessing the empirical data. Therefore, using simulation techniques can be more notable for overcoming this obstacle. Simulation parameters and algorithms need to follow the research framework to achieve desirable results. The realistic simulation design can provide data to evaluate and redesign the research framework [25, 81, 92]. In this section, supply chain resilience studies using simulation tools to evaluate their framework are reviewed. The focus is on studies that have focused on simulation techniques to assess supply resilience and mitigate potential risks.

A recent study [81] developed a methodology to define the critical factors that can reduce or increase the impact of direct and indirect disruption on a supply network. The authors combine the structured experimental design with a discrete simulation. The study shows that inter-arrival time, connectivity, and buffering of stocks are essential factors to alleviate any disruptions. Simulation models have been developed in the literature

to evaluate the supply chain resilience level and provide the optimal recovery strategies; for instance, a three-tier automotive supply network using real data has been simulated to evaluate two recovery strategies regarding six given disruption scenarios [49]. The authors demonstrate how these disruptions scenarios and mitigation strategies can impact each supply chain entity's performance. Two performance metrics, lead-time ratio and total cost for each entity are used to measure the resilience level. Also, in another study, a pharmaceutical supply chain has been simulated to analysis the resilience and detect the trade-off between three recovery strategies, which can be a function of disruption parameters (such as its severity and duration). The authors tracked the resilience level by measuring out of stock inventory and unsatisfied demand [76]. Dmitry Ivanov [59, 60] observes and predicts the behavior of the supply chain during disruption using discrete event simulation models. The author states that additional information (such as disruption features or regional information) can be useful to optimize the supply network. For the entire supply chain, it is critical to evaluate and analyze the whole supply network instead of considering simple dyadic relationships between suppliers and manufacturers. A few studies have integrated the simulation and network analysis to improve the accuracy of supply resilience assessment [122,135]. To fill this gap, social network analysis techniques and discrete-event simulation are used to assess the level of a sophisticated supply chain.

2.3 Resilience Assessment Framework

In this section, we present details about the proposed supply network resilience assessment framework along with preliminary results from an illustrative case study informed by a real-world automotive supply network. The section includes the description of simu-

lation settings and resilience assessment.

This research seeks to propose an effective resilience assessment framework for deep-tier supply networks utilizing historical data and secondary data sources. The proposed methodology, shown in Fig. 12 with six main components, aims at assessing the resilience of supply chain networks representing various industries and commodities with diverse structures and complexities when exposed to disruptive events. First, network components, regional risk, operational, and historical disruption data combined with information from domain experts (data acquisition) are injected to ‘Supply Network’ and ‘Scenario Planning’ modules. In the data acquisition phase, any available historical recorded data is combined with secondary data sources from third-parties and guidance from domain experts to reach a more accurate resilience assessment framework. The ‘Supply Network’ module creates the appropriate network structure based on the input data regarding supply network structure and policies. Disruption sources and parameters, including frequency, intensity, and duration for scenarios planning are also acquired using historical and secondary data. The ‘Scenarios Planning’ component is responsible for identifying the optimal set of scenarios for carrying out the resilience assessment, and notifies the disruption simulator to carryout the necessary simulations. The task of the ‘Disruption Simulator’ is to efficiently carryout the necessary simulations and pass the observed outcomes to the ‘Resilience Assessment’ module. Finally, the ‘Resilience Assessment’ module utilizes both operational metrics as well as impact assessment data to characterize overall supply network resilience, considering its multi-dimensional perspective. The ‘Global Sensitivity Analysis’ of the uncertain parameters is critical to prioritize additional data collection efforts and provide more actionable guidance to supply chain managers.

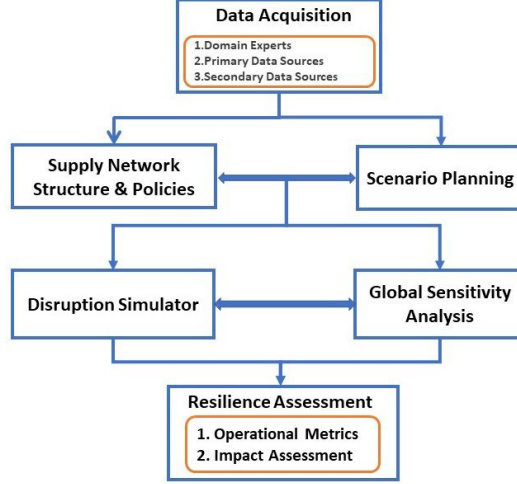


Figure 1: Resilience assessment methodology

An overview of the notation used throughout this paper is provided in Table. 6.

2.3.1 Supply Network Structure & Policies

A supply network is a collection of temporal and spatial processes carried out at facility nodes and over distribution links. It adds value for customers through manufacturing and delivery of products. The types and numbers of supply network components can make it complex to employ more accurate analysis for resilience assessment. In the first step of our method, the supply network component maps a deep-tier network, consisting of links and nodes denoted by E and N , indexed by e and n , respectively. The network includes different types of nodes: focal firm, denoted by F , located in the center of the network, suppliers, warehouses, distribution centers, and ports located in different up-stream and down-stream tiers. The focal firm sources parts and materials from tier-1 nodes. Each tier-1 node, in turn, sources intermediate parts and components from tier-2; and this repeats through other tiers. For a given node n in the network, I_n represents a set of direct supplier nodes, and U_n represents a set of customer nodes. The granularity of supply network representation should depend on the size of the network, quality and

| Sets | |
|---------------------------|--|
| N | Set of nodes for a given network, indexed by $n \in N$ |
| E | Set of edges for a given network, indexed by $e \in E$ |
| I_n | Set of customer nodes for node n , indexed by $i \in I_n$ |
| U_n | Set of supplier nodes for node n , indexed by $u \in U_n$ |
| W | Set of supply chain tiers, indexed by $w \in W$ |
| T | Set of simulation time slots within the planning horizon, indexed by $t \in T$ |
| Variables | |
| x_{unt} | Inventory level of part supplied by supplier u for node n , in time t |
| a_{unt} | Quantity of part shipped by supplier u to node n , in time t |
| b_{unt} | Backorder level of part supplied by supplier u for node n , in time t |
| y_{unt} | Quantity of order placing from node n to node u at time t |
| z_n | Demand resilience level for node n |
| Parameters | |
| θ | Number of simulation replications |
| c_n | Total inventory cost for node n |
| p_n | Total Backordered cost for node n |
| o_{un} | Inventory cost per day per part from supplier u at node n |
| v_{ni} | Backordered cost for customer i of node n |
| ϕ_{un} | Initial inventory level of part supplied by supplier u at node n |
| s_n | Finished good safety stock for node n |
| l_e | Shipment lead time of edge e |
| h_e | Shipment frequency of edge e |
| m_{un} | Periodic review policy of part supplied by supplier u for node n (days) |
| d_{Ft} | Daily demand for focal firm at time t |
| k_{int} | Demand from customer i for node n at time t |
| γ_{un} | Usage rate of part from supplier u at node n |
| g_{un} | Restocking level of part supplied by supplier u at node n |
| α_n | Disruption duration for node n |
| q_n | Disruption intensity for time disruption (α_n) for node n |
| f_n | Disruption frequency for node n |
| r_n | Regional risk index for node n |
| Network components | |
| S_{nw} | Supplier n in tier w |
| F | Focal firm |

Table 1: Nomenclature

ease of information sources, and planning/modeling resources available for assessment. Generally, one can expect diminishing benefits from increasing the granularity of modeling beyond a certain level. For the purposes of supply network resilience assessment, at a minimum, each node n should be characterized by target raw material inventory level (o_{nu}) and finished goods inventory (s_n), as well as processing cycle time. Also, links between nodes are unidirectional to denote the one-way flow of products. Links have attributes such as shipment mode, lead time (l_e) and shipment frequency (h_e).

2.3.2 Disruption Scenarios

The supply chains are not immune from disruptions, which are the unfavorable changes in the regular operations. Without any disruption, on-hand inventory will generally be adequate to meet demand at any node within the supply network. So, the disruption scenarios component lies at the center of our framework. The inputs are network topology and settings for generating disruptions, and the output is scenario settings. Simulator receives scenario setting as its input, such as the numbers of nodes/linked need to be disrupted, disruption intensity q_n , frequency f_n , and duration α_n for each of the nodes in network based on their regional risk (r_n). Then, disruption scenarios are simulated through a specific planning horizon.

2.3.3 Resilience Assessment

The resilience curve which is illustrated in Fig. 2 is adopted by various research studies including inventory control theory [127], transportation system [47], power system [133], and information security [71]. A system performance indicator $P(t)$ is used to quantify the system resilience level during a time period t . As shown in the Fig. 2, the resilience curve possesses four transition stages describing the system behavior over time. A brief

description of these stages is as follows:

- Reliability (S1): This is the stage when there is no disruption and the network or system operates in a healthy state.
- Unreliability (S2): This is the stage of degradation, when a disruption(s) accrues in the period $[t_d, t_r]$ and system performance drops to P_v due to partial loss of functionality.
- Recovery (S3): This is when the network or system starts to recover its performance, relying on any appropriate recovery policies.
- Recovered (S4): The system reaches a stable level in t_e depending on the disruption severity and duration. The system can recover to original performance, sustain permanent deterioration, or can reach improved performance due to corrective actions.

The impacted area (IA) shown in Fig. 2 captures in aggregate the severity of disruption events combined with the effectiveness of recovery policies and guides us in characterizing system resilience. The supply chain studies have endorsed various performance measures including service level, network capacity, delivery time, inventory level, and system throughput for resilience assessment [53]. Without any disruption, on hand inventory will generally be adequate to meet demand at any node within the supply network. But in the presence of a disruption, the orders can be backlogged and demand may not be fully satisfied due to deterioration of system functionality.

If one were to employ demand satisfaction/coverage as the metric of interest, we can quantify the resilience level (RSL) of each node (or firm) by integrating and averaging

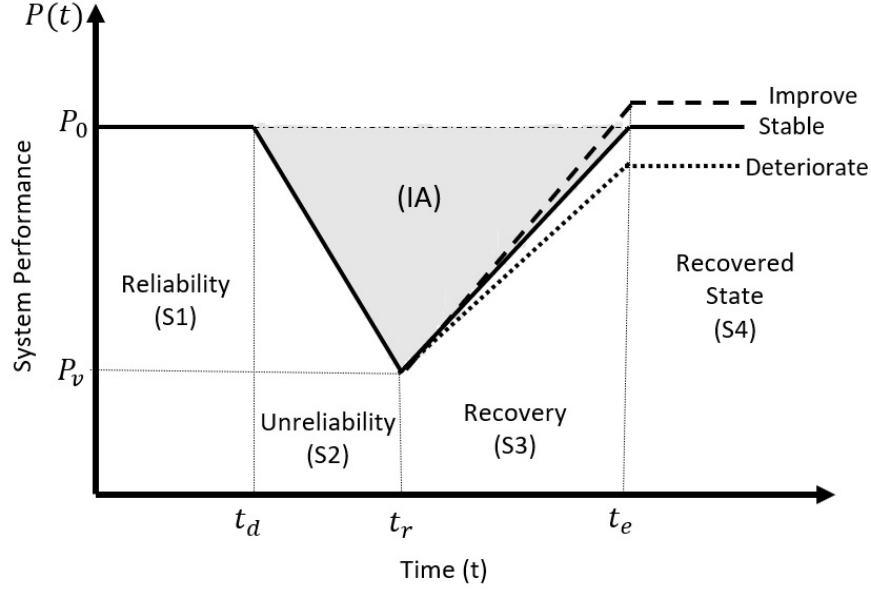


Figure 2: Resilience curve illustrates system performance under disruption and its stages.

coverage over all data collection time steps as follows [47]:

$$RSL = \frac{\sum_{t=0}^T (1 - \frac{LoD_t}{ToD_t})}{T}. \quad (2.1)$$

Here LoD_t and ToD_t represent lost and total demand at the particular node of interest for each time unit t (e.g., day or week), respectively, and the quantity $\frac{LoD_t}{ToD_t}$ represents the impacted area (IA). The data collection window could involve multiple disruption and recovery cycles and T is duration of the data collection period ($RSL \in [0, 1]; t \in [0, T]$). Note that this approach could also be employed for characterizing supply network resilience for any given node even if we were to employ simulation for evaluating different supply network designs/configurations.

2.3.4 Deep-Tier Network Visibility

Given that majority of supply chain disruptions stem from deep-tier suppliers and not the tier-1 suppliers [6], any resilience assessment scheme should carefully investigate the impact of deep-tier network visibility on the true network resilience. Without the loss of generality, we recommend four visibility scenarios:

- **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.
- **Limited Visibility** (SC1): Network visibility limited to tiers-1 & 2; Assumes upstream suppliers are perfectly reliable.
- **Typical Scenario** (SC2): Network visibility limited to tier-1 suppliers.
- **No-risk Scenario** (SC3): Assumes that the entire supply network is immune to disruptions.

2.3.5 Identifying Deep-Tier Suppliers

As noted earlier, it is reported that over half of all supply chain disruptions indeed stem from tier-2 and tier-3 suppliers [6]. A common approach to overcome this visibility limitation is to request tier-1 suppliers to share information regarding their supply base [29]. While most suppliers tend to guard such information carefully, contracts can be set up to require suppliers to share critical information. For instance, after the March 2011 earthquake and the devastating supply disruptions, Toyota leveraged its strong supplier relationships to acquire critical information to develop the REinforce Supply Chain

Under Emergency (RESCUE) system [120]. This system maintains parts information for around 650,000 supplier sites to diminish disruption damages for all key commodities. If any disruption occurs, Toyota can rapidly detect which suppliers and parts are at risk and deploy contingency actions [7]. An alternative would be to work with third-party information aggregators such as Bloomberg Supply Chain Database [15], Marklines [83], and IHS Markit [57] that provide vital information regarding deep-tier supply networks for select industries and regions of the world. The information available through secondary sources for suppliers across various industries can include the number of production sites and their geographical locations for different product families, customer firms for different product families, quality of production and distribution infrastructure, socio-political and economic data, and overall regional risk indexes. The quality of these databases and their resolution could vary based on industry and region. For example, while Marklines covers over 50k automotive parts supply companies, it provides much better supplier coverage within Asia. It also provides information on who supplies who for around 300 major components like automatic transmissions, air conditioners, seats, and navigation systems in Japan, Europe, the U.S., China, India, and more.

As for the automotive OEM case study discussed in the manuscript, besides data from the OEM, secondary data from IHS Markit [57] and World Port Source [125] were used to map and model supply network resilience. See additional details in Table 2.

2.3.6 Sensitivity Analysis

Multiple parameters can be uncertain during supply network (re-)design, and decision-makers try to obtain more information to understand the implications of these uncertainties. In the context of supply network resilience assessment, Sensitivity Analysis (SA) can

| Information Type | Data Source | Note |
|----------------------|-------------------|--|
| Suppliers | OEM | Details regarding all tier-1, -2, and -3 suppliers along with their locations and capacities. |
| Transportation | OEM | Modes of transportation (including truck, rail, boat, air) for each arc of the supply network, frequency of shipments and their lead-times. |
| Regional Risk Scores | IHS Markit | The frequency and severity of disruptions expected from the different supplier facilities within the case study are based on regional risk scores identified by IHS Markit (details in section 4.2). While facilities within a region can exhibit different levels of resilience, the case study strictly relied on risk scores from IHS Markit. |
| Shipping Ports | World Port Source | The exact locations of the shipping ports were identified using information from the World Port Source. |

Table 2: Summary of data used to map and model the deep-tier automotive supply network

help us in quantifying the impact of uncertain parameters (denoted by X , the vector of uncertain inputs) on the variance of performance metrics (denoted by Y). Uncertainty could be around regional risks, operating policies of upstream suppliers, and so on. Any effective supply network resilience assessment scheme should incorporate proper SA to prioritize additional information collection efforts and reduce overall risk and uncertainty.

Overall, SA serves three primary purposes in supply network resilience assessment: 1) identifying the key supply network's topological features; 2) identifying the relationship (positive or negative) between different key parameters/factors on the network performance; and 3) determining the most important parameters (e.g., suppliers and operating policies).

While the literature offers several methods for SA, we recommend variance-based and moment-independent approaches due to their computational efficiency and effectiveness [106]. The variance-based SA approach is a technique that decomposes the output variances into fractions that can be attributed to inputs or set of inputs. The main advantage is computing the "Total Sensitivity Index" obtained from the sum of all the sensitivity

indices involving any particular variable. Variance-based importance measures are defined as follows in eq.(2.2) [52, 58, 97]:

$$SI_i = \frac{V_Y - \mathbb{E}_{X_i}[V_Y|X_i]}{V_Y} = 1 - \frac{\mathbb{E}_{x_i}[V_Y|X_i]}{V_Y}, \quad (2.2)$$

where X_i denotes the i th uncertain input parameter, Y the output metric of interest, V_Y represents the output variance, $\mathbb{E}_{x_i}[V_Y|X_i]$ is the conditional expected value of V_Y given X_i , and SI_i is the sensitivity index of each uncertain parameter.

For conducting the sensitivity analysis without relying on any particular moment of output Y , the moment-independent SA techniques have been introduced [16, 100]. The moment-independent sensitivity, which is called Delta (δ), is defined as follows:

$$\delta_i = \frac{1}{2} \mathbb{E}_{x_i}[s(X_i)], s(X_i) = \int |f_Y(y) - f_{Y|X_i}(y)| dy, \quad (2.3)$$

where $s(X_i)$ measures the distance between $f_Y(y)$ and the conditional density function of Y , given one of the inputs.

2.3.7 Simulation Model

As discussed earlier, discrete-event simulation is employed as the primary methodology for resilience assessment. Details for the significant simulation steps and the order of events are provided in Algorithm 2. Once the network is configured (Step 1) and initialized with a starting state (Step 2) and assigned proper operating (Steps 3 & 4) parameters, under any given scenario, the full supply network is simulated for $T=700$ days with a

warm-up period of 3 months (90 days), representing roughly 2-years of operation. As noted earlier, the final focal firm F production volume is assumed to be exogenous and follows a normal distribution. During the simulation, disruption frequency and intensity for each node are obtained based on their regional risk index (Step 4). Ordering process and shipments are simulated (Step 5) with tracking the product flows, delays, and costs in detail on a daily basis for supply network resilience assessment.

To study the impact of deep-tier network visibility on resilience assessment, we evaluated the case study supply network under all the visibility scenarios. For improved assessment accuracy, each simulation scenario is replicated ten times and all the results reported in the rest of the manuscript are averages.

SimPy is used for implementing discrete-event simulation and NetworkX is utilized to generate and analyze the network. A personal computer with Intel Core i5-6300U CPU (2.4 GHz) with 8.00 GB RAM has been used for our case study. In the following subsections, we first discuss results from different visibility and other scenarios, followed by a brief discussion of significant managerial insights obtained from our study.

Algorithm 1: Supply Network Simulation Model

- 1 **Step 1:** Load supply network configuration: Nodes (N) and edges (E).
- 2 **Step 2:** Load inventory policy for each node n : Raw material initial inventory (ϕ_{un}) and finished good safety stock (s_n), restock level (g_{un}) for part u follows:

$$g_{un} = (\sum_{i \in I} \sum_{t=m_{un}}^{m_{un}+l_e} k_{int} + s_n) \gamma_{un} \quad e \in \forall[n, i].$$
- 3 **Step 3:** Load transportation parameters for each edge e : Shipment lead time (l_e) and shipment frequency (h_e).
- 4 **Step 4:** Load disruption parameters for each node n : Regional node risk (r_n), disruption intensity (q_n), disruption frequency (f_n), and disruption duration (α_n).
- 5 **Step 5:** For $t \in T$
 - 6 Observe daily demand for focal firm: $d_{Ft} = \mathcal{N}(\mu, \sigma^2)$.
 - 7 **For** $n \in N$
 - 8 **For** $u \in U_n$: Simulate disruption process:
 - 9 **If** $t \% f_n = 0$ and $q_n \geq 0$: node n is disrupted for duration α_n
 - 10 **Else** no disruption and $q_n = 0$:
 - 11 Simulating ordering process (periodic review):
 - 12 **a) If** time for ordering and $x_{unt} \leq g_{un}$:
 - 13 place orders for each supplier, $y_{unt} = (g_{un} - x_{unt})$
 - 14 **b) If** Order receive from supplier u and $a_{unt} \geq 0$:
 - 15 update inventory level at node n , $x_{unt} = x_{unt-1} + (1 - q_i)a_{et}$,
 $e \in [u, n]$
 - 16 simulating transportation:
 - 17 **If** time for shipping ($t \% h_e = 0$, $e \in [u, n]$) and $y_{unt} \geq 0$: perform
 shipping from each supplier u to node n
 - 18 update inventory level at supplier u :
 $x_{unt} = x_{unt-1} - (1 - q_n)a_{et}$, $e \in [u, n]$
 - 19 **End for** Calculate back-orders and shipment delays
 - 20 **End for** Calculate demand fulfillment resilience level z_n
 - 21 **End for**
 - 22 **Step 7:** Calculate costs for each node n : Holding cost $c_n = \sum_u \sum_t o_{n\psi} x_{unt}$, and
 back-order cost $p_n = \sum_u \sum_t \nu_{ni} b_{unt}$.

2.3.8 Disruption Modeling

In the absence of detailed disruption models or data for the different node facilities and transportation arcs of the case study supply network, the following logic is employed to model and simulate disruptions for supply network resilience assessment:

- Risk index for specific facilities within a region are assumed to follow a distribution centered around the regional risk index data obtained from IHS Markit. In particular, overall risk scores are calculated as equally weighted averages of the six aggregate risk factor categories outlined in Fig. 3. Overall, the IHS Markit risk index is scored on a 0.1-10 logarithmic scale. The overall range is split into four bands, ranging from low to extreme risk (Fig. 5).

| Political | Economic | Legal | Tax | Operational | Security |
|------------------------|-------------------|------------------|-----------------|---------------------------|----------------|
| Government instability | Recession | Expropriation | Tax increase | Corruption | Protests |
| Policy instability | Inflection | State alteration | Tax instability | Regulatory burden | Terrorism |
| | Currency transfer | | | Labor strikes | Interstate war |
| | Capital transfer | | | Infrastructure disruption | Civil war |
| | Sovereign default | | | | |

Table 3: Risk factors considered by IHS Markit in estimating regional risk index. (Source: IHS Markit 2020)

- Given the facility's risk index based on the regional risk index, disruption frequency and intensity can be estimated for example by interpolating the risk matrix. Horizontal-axis frequency value of 1% could correspond to an average disruption once every 100 weeks, and 10% corresponds to an average disruption once every ten weeks. As for interpolating frequency and intensity parameters from the given risk index, here is an example. Suppose for a given node risk index (r_n) is 4 (falls into 'High Risk'

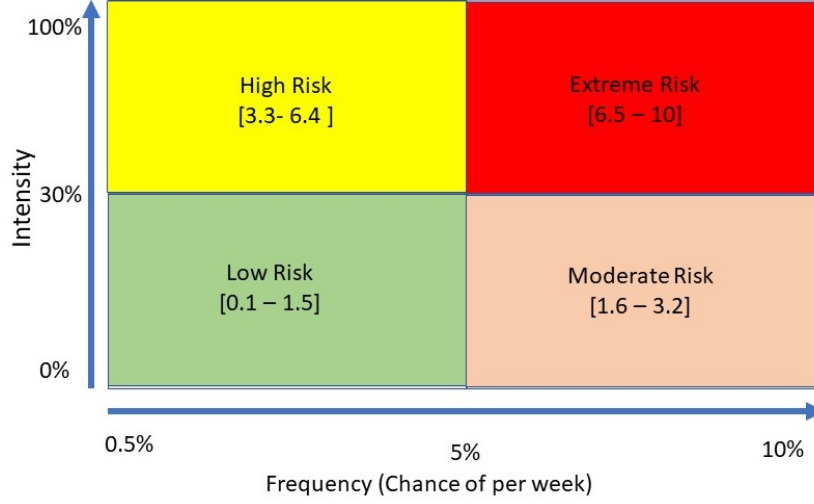


Figure 3: Risk Matrix of the four risk categories to obtain disruption frequency and intensity.

yellow section of Fig. 3 with an index range of [3.3-6.4]) with horizontal-axis disruption frequency support of [0.5%-5%] and vertical-axis disruption intensity spanning [30%-100%]. We first calculate the disruption index ratio λ as a function of given risk index score for index support (i.e., [3.3-6.4]):

$$\lambda = \frac{r_n - 3.3}{6.4 - 3.3} = 0.22$$

Given the disruption index λ , disruption frequency and intensity for the specific node can be interpolated as follows:

$$f_n = (0.05 - 0.005) \times \lambda + 0.005 = 0.015$$

$$q_n = (1 - 0.3) \times \lambda + 0.3 = 0.45$$

Disruption duration (α_n) can be short or long. In our case study, we assumed that short and long-duration disruptions follow a uniform distribution with parameters $\mathcal{U}[4,7]$ and $\mathcal{U}[8,14]$ days, respectively.

2.4 Case Study Setting

The supply network for an automotive climate control system (Fig. 4) has been chosen to demonstrate the applicability of the proposed deep-tier approach in the automotive industry. The network is mapped with different types of nodes: assembly plants/focal firm (white), warehouses (white), tier-1 suppliers (black), tier-2 suppliers (blue), tier-3 suppliers (yellow), and ports (white) with different transportation modes. The network possesses 21 nodes and 20 edges, and shipping information (shipping time / shipment frequency) are reported on the edges. Node connectivity and geographical locations are also reported in the figure. For instance, the link between supplier S17 and the focal firm has the shipping information ($\frac{1}{2}H/32D$), meaning that shipping frequency is 32 times a day with a half-hour delivery time, or shipments between S13 and focal firm ($3D/1D$) happens once in a day, and each shipment takes three days. Nodes (or firms) are located in different geographical zones, and the geographical distance (in miles) between two connected nodes is used as the “weight” for the edge. The supply network contains two suppliers who are located in France and South Korea that deliver parts via ship and truck (multi-modal). Other nodes are located in Mexico and the USA, which deliver their products by truck in a range of half hour to six days. Part names for each supplier are also reported in the figure. For example, the compressor and Hex pipes are shipped by suppliers S33 and S22, respectively. Final assembly plant demand is estimated based on historical data. Final assembly plant and its suppliers (tier-1, -2, and -3) and assumed to employ (s,S) inventory policy. During simulation, the inventory levels at suppliers, assembly facility, warehouses, ports, or in transit is recorded for each time step for analysis. See Appendix.A for full details

about inventory policy parameters, transportation lead-times and safety stock.

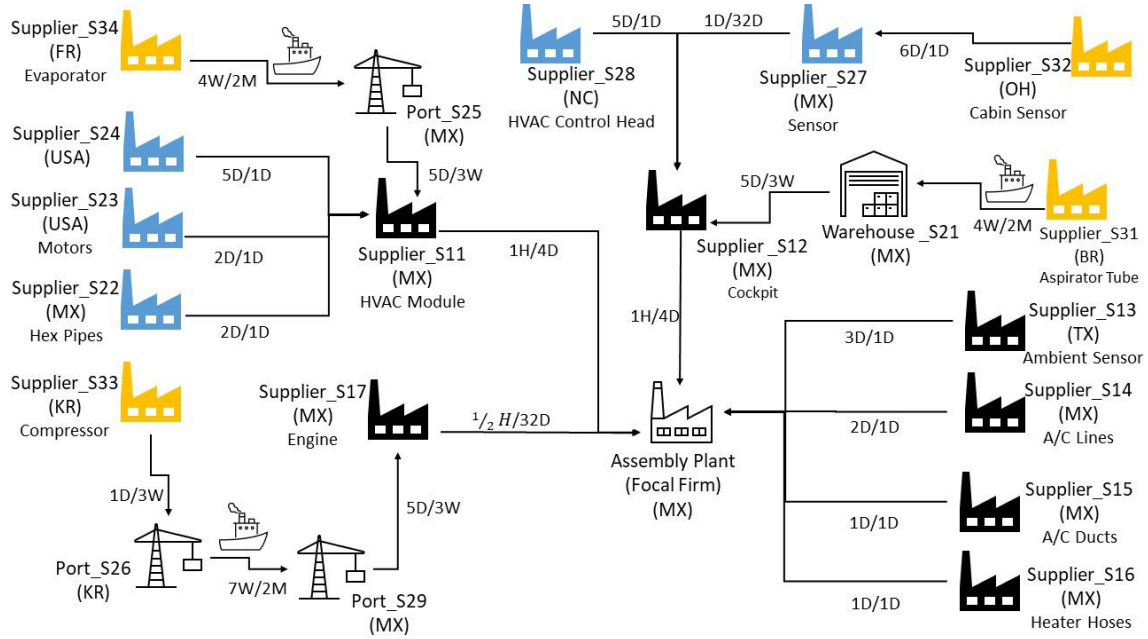


Figure 4: Case study supply network for an automotive climate control system.

FR: France, KR: South Korea, MX: Mexico, BR: Brazil, TX: Texas-US, NC: North Carolina-US, OH: Ohio-US
H: hours, D: days, W: weeks, M: months.

A “risk index” is incorporated into our study to address the overall supply risk imposed by nodes located in challenging regions. Based on geographical location and its corresponding geopolitical, legal, and economic changes, regional risk indices are available from several sources. For illustrative purposes, here we employ the risk indices available from global information provider IHS Markit and reported in (Fig. 5) [57]. Nodes of case study are located in France, South Korea, Mexico, Brazil, and the USA with risk index 1.7, 1.5, 2.7, 2.5, and 1.6, respectively (lower the index, lower the risk). These indices are employed for emulating disruptions during simulation as explained earlier.

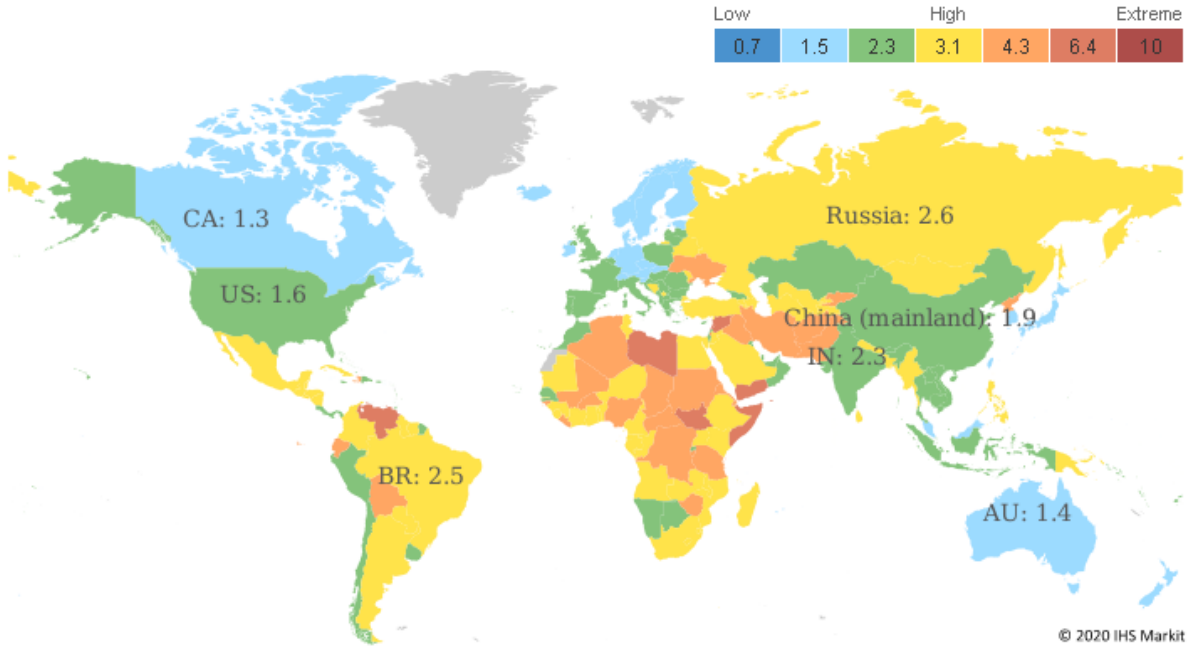


Figure 5: IHS Markit's unique country risk - Last updated for Q2-2020

2.5 Experimental Results and Analysis

To test the hypotheses outlined earlier, we simulated the case study supply network under each of the four scenarios (SC0, SC1, SC2, and SC3) for 700 days ($T=700$ days) and with 10 replications.

2.5.1 Impact of Visibility on Resilience Assessment

Table 4 and Fig. 6 report the estimated average node resilience levels across replications under the different scenarios (i.e., different levels of deep-tier visibility). Resilience assessment is carried out here by employing Eq.2.1.

Several observations can be made from Table 4. Under limited upstream visibility, we can significantly overestimate node resilience and develop a false sense of security. For the focal firm, the estimated resilience jumps to 70.75% and 85.36% from 63.86%,

| Node | Focal Firm | S11 | S12 | S13 | S14 | S15 | S16 | S17 | S21 | |
|------|------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| RL | SC0 | 63.86 | 71.17 | 86.57 | 89.85 | 87.89 | 74.75 | 75.74 | 68.49 | 96.03 |
| | SC1 | 70.56 | 83.45 | 89.92 | 94.77 | 90.63 | 79.84 | 80.41 | 72.34 | 100 |
| | SC2 | 85.36 | 97.91 | 96.94 | 100 | 97.9 | 87.91 | 88.03 | 97.91 | NA |
| DC | | 7 | 5 | 4 | 1 | 1 | 1 | 1 | 2 | 2 |

| Node | | S22 | S23 | S24 | S25 | S26 | S27 | S28 | S29 |
|------|-----|-------|-------|-------|-------|-------|-------|-------|-------|
| RL | SC0 | 86.83 | 92.32 | 92.66 | 86.26 | 79.78 | 87.65 | 92.44 | 81.10 |
| | SC1 | 100 | 97.66 | 95.21 | 98.53 | 87.07 | 96.72 | 97.22 | 95.54 |
| | SC2 | NA | NA | NA | NA | NA | NA | NA | NA |
| DC | | 1 | 1 | 1 | 2 | 2 | 2 | 1 | 2 |

RL (Resilience Level); SC (Scenario); DC (Degree Centrality)

Base Scenario (SC0): Visibility to all three tiers of the case study network.

First Scenario (SC1): Visibility to just tier-1 and tier-2 suppliers.

Second Scenario (SC2): Visibility limited to just tier-1 suppliers, typical of most companies.

Table 4: Estimated node resilience under different levels of upstream visibility.

when we restrict visibility to just tier-2 and tier-1 suppliers, respectively. Scenario ‘SC0’ represents the complete supply network containing 21 nodes and 20 edges (tiers-1, -2, and -3 suppliers), whereas ‘SC1’ scenario network carries not tier-3 suppliers and their connections (possesses 17 nodes and 16 edges). Finally, the ‘SC2’ scenario network has only tier-1 suppliers and their corresponding connections.

Extant supply network assessment literature does highlight the importance of node degree centrality in identifying network vulnerabilities. Unfortunately, degree centrality can vary a great deal based on the function of the node (e.g., warehouses by definition tend to carry very high centrality). While correlation between centrality and estimated resilience should be expected, node centrality measure is not adequate for proper resilience assessment. Degree centrality for each node of the case study network is also reported in Table 4. It shows that supplier S_{11} , with the highest degree centrality, does exhibit significant differences in estimated resilience under different visibility scenarios. Supplier S_{23} exhibits the lowest degree centrality with the highest resilience changes, followed by

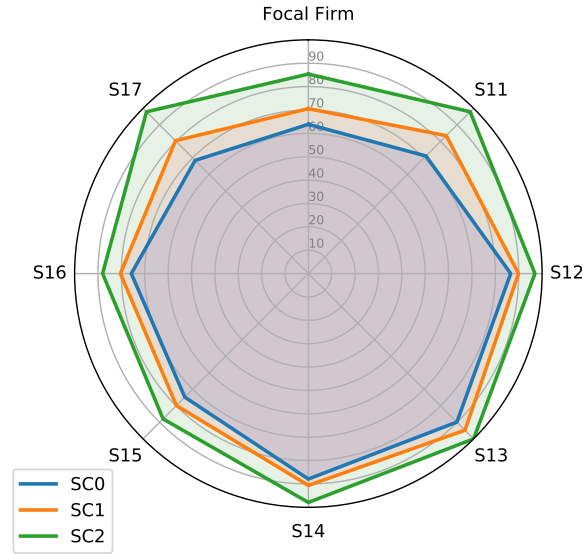


Figure 6: Estimated node resilience for focal firm and tier-1 suppliers under different levels of upstream visibility. [Full Visibility Scenario (SC0), Limited Visibility Scenario (SC1), Typical Scenario (SC2)]

Supplier S_{24} . It can be concluded that nodes with a high degree of centrality are critical and vulnerable. However, comparing the resilience level of S_{17} and S_{21} with both carrying 2-degree centrality shows that other factors can also impact resilience. Two suppliers with the same degree of centrality exhibit two different behaviors; supplier S_{17} demonstrates more resilience changes than supplier S_{22} . It indicates that supply chain parameters such as inventory policy, shipment modes, and shipment frequency of each node need to be considered. Just employing simple static network analysis metrics is not adequate for reaching good resilience assessment accuracy.

Fig. 7 reports sample estimated order service level history for focal firm, tier-1 supplier S_{11} with high centrality, and tier-1 supplier S_{13} with low centrality under different levels of deep-tier visibility from a particular simulation run. Under limited deep-tier visibility, we significantly overestimate order service level both for the focal firm as well as the tier-1

suppliers. It also shows that the focal firm and supplier S_{11} with high centrality experience more volatility in the service level.

2.5.2 Impact of Deep-Tier Visibility on Supply Cost and Responsiveness Assessment

Supply network resilience requires exploring multidimensional metrics. The structural, operational, and resilience levels require to be investigated to develop a comprehensive analysis. Making a decision-based all potential factors such as cost, shipment delay, lead time, backordered, and profit margin could benefit the supply chain network and mitigate disruption consequences. Developing the overall view of supply chain performance can provide more practical solutions and strategies. This section analyzes holding and back-order costs estimated for the focal firm under different levels of deep-tier visibility. We also track on-time order delivery performance by each of the tier-1 suppliers under different

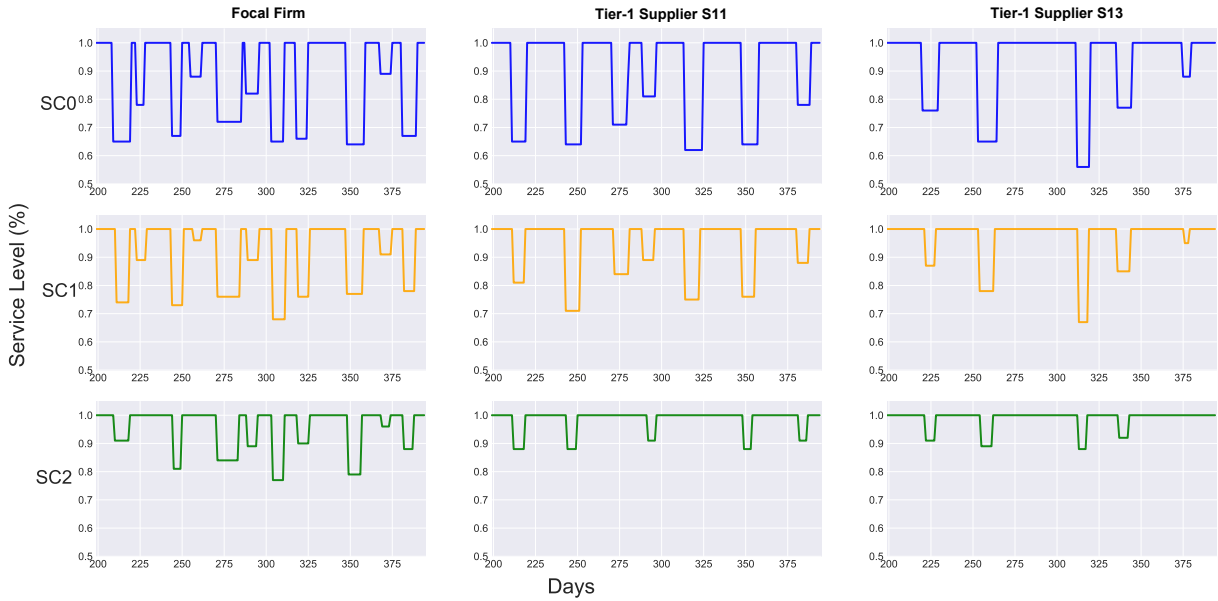


Figure 7: Sample estimated order service level history for focal firm, tier-1 supplier S_{11} with high centrality, and tier-1 supplier S_{13} with low centrality under different levels of deep-tier visibility. [Full Visibility Scenario (SC0), Limited Visibility Scenario (SC1), Typical Scenario (SC2)]

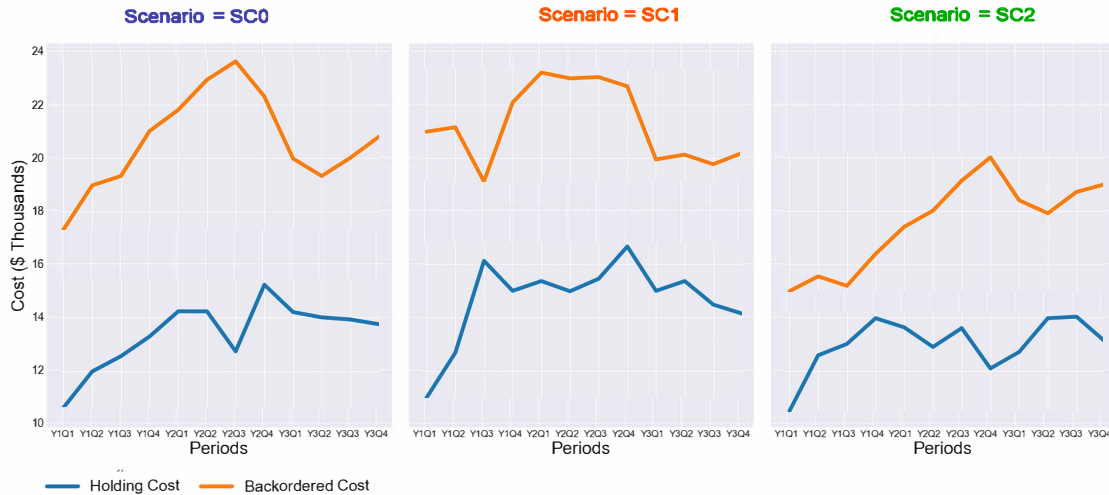


Figure 8: Sample estimated holding and back-order cost history for focal firm under different levels of deep-tier visibility. [Full Visibility Scenario (SC0), Limited Visibility Scenario (SC1), Typical Scenario (SC2)]

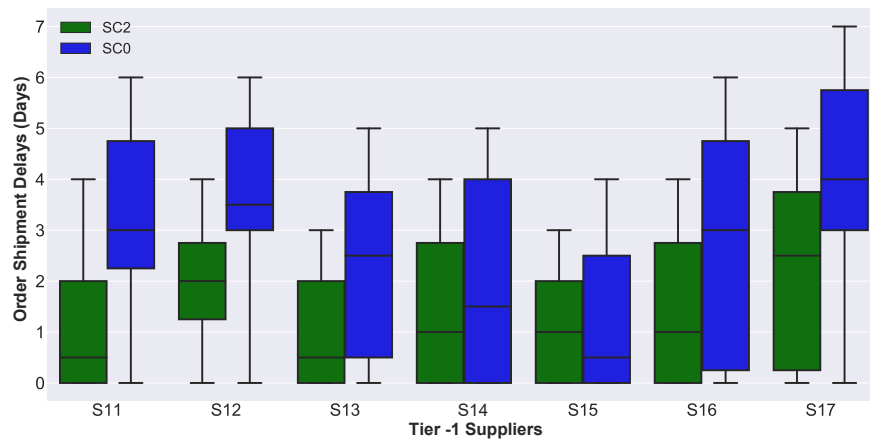


Figure 9: Estimated order shipment delays by tier-1 suppliers under two different visibility scenarios. [Full Visibility Scenario (SC0), Typical Scenario (SC2)]

levels of visibility.

Fig. 16 tracks the estimated back-order and inventory holding costs for the focal firm under three levels of deep-tier visibility for each quarter (three months) during one simulation run. It is clear that costs are significantly underestimated when assessment is carried out with reduced deep-tier visibility.

Fig. 9 reports the distributions for the order delivery lead-time delays experienced un-

der different levels of upstream visibility. For example, supplier *S11* can have a maximum of 12 days delay on delivery parts to the focal firm when we map and consider all three tiers. Under limited visibility to just tier-1 suppliers, the maximum delay delivery is estimated to be just 6 days. Other tier-1 suppliers show similar behaviors as well. Deep-tier visibility can lead to a more realistic assessment of delivery performance for improved management.

2.5.3 Impact of Consideration for Regional Risk on Resilience Assessment

To demonstrate the importance of accounting for differences in regional risks, we now compare the results from two scenarios: *SC0* - Accounts for differences in regional risks; *SC3* - Assumes that all nodes of the supply network carry similar and reasonably low risk. Fig. 10 reports the differences in resilience assessment results from the different simulation runs under the two scenarios. Ignoring regional risk differences causes us to overestimate resilience for the focal firm by about 6%. We also see significant differences for several suppliers. The increase can be attributed to consideration differences in regional risks as well as the interaction of the resulting disruption patterns on operation policies of the supply chain, as listed in Table 5.

| | Risk index | %RL | Comment |
|-------------------|------------|--------|--|
| Focal Firm | 2.5 | 17.31% | Risk: Six suppliers located in Mexico with risk index 2.5 and 1 US supplier with risk index 1.6. |
| T11 | 2.5 | 9.13% | Risk: Two suppliers located in Mexico with risk index 2.5 and 2 US suppliers with risk index 1.6. Performance: 5 days of delay in delivery from T34 to T11. |
| T12 | 2.5 | 8.23% | Risk: Two suppliers located in Mexico with risk index 2.5 and one US supplier with risk index 1.6. Performance: 6 days of delay in delivery from T31 to T12 with lack of adequate inventory at T12. |
| T14 | 2.5 | 6.22% | Risk: One supplier located in Mexico with risk index 2.5. Performance: Very low shipment capacity and inventory. |
| T17 | 2.5 | 17.62% | Risk: One supplier located in Mexico with risk index 2.5. Performance: 9 days of delay in delivery from T33 to T17 with low inventory level for T17. |

Table 5: Summary of reasons for major changes in estimated resilience level under consideration of regional risk indices.

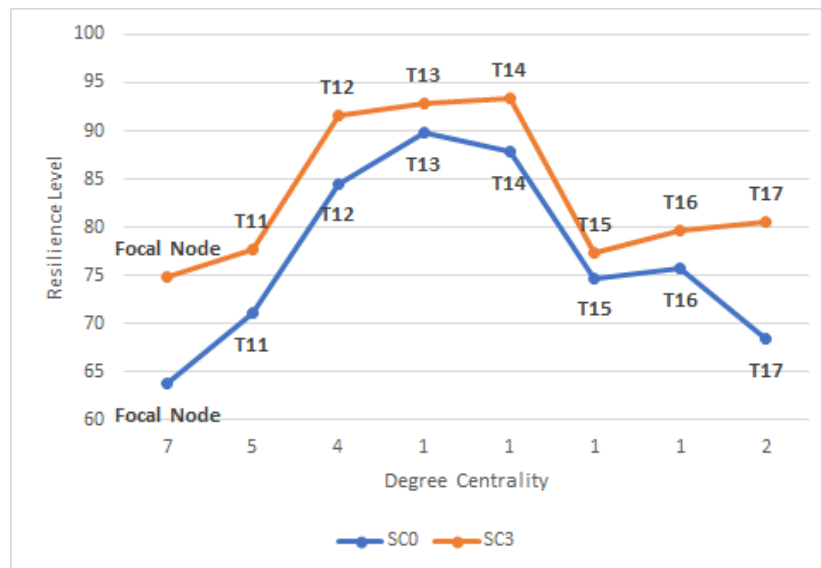


Figure 10: Differences in assessed resilience level with and without consideration for differences in regional risk indices (Scenarios 'SC0' vs 'SC3') along with node degree centrality.

These results confirm that network resilience assessment should be performed by carefully considering deep-tier visibility, regional/firm risk differences, and impact of supply

chain operational policies. Thus, the supply manager should utilize this guidance to design a network to minimize cost and obtain acceptable resilience levels.

2.6 Sensitivity Analysis

Multiple parameters can be uncertain in supply chain problems and decision-makers try to obtain more information to reduce the uncertainty. As noted earlier, SA aims to enrich the proposed resilience assessment framework by capturing the factors that influence simulation output.

Here, for illustrative purposes, we particularly investigate the sensitivity of focal firm's resilience as a function of uncertainty in regional risk indices for the different suppliers. The regional risk indices for individual suppliers are considered random parameters and we hold the other supply network parameters to be constant during SA. In particular, the regional risk indices are allowed to follow a normal distribution with a coefficient of variation of 0.5 (i.e., σ/μ) and the mean (μ) is set to be regional risk indices available from IHS Markit.

Results from both the variance-based sensitivity index (SI_i) as well as the moment-independent Delta (δ_i) techniques are reported in Fig. 11. While the results from the two methods vary a bit, they are directionally very consistent in identifying suppliers S_{11} , S_{17} , S_{12} , S_{13} , and S_{25} to be key for effective network resilience for the focal firm. Such an analysis can help supply chain managers prioritize their efforts and devote more resources for studying the key suppliers, data collection and parameter estimation. The critical suppliers, such as S_{11} and S_{12} , possess a high centrality degree, which confirms they need to be considered essential suppliers. Suppliers S_{17} and S_{25} are connected to overseas tier-2 and

tier-3 suppliers, located in a risky geographical location, and are also vulnerable to long transportation lead-time delivery cycles.

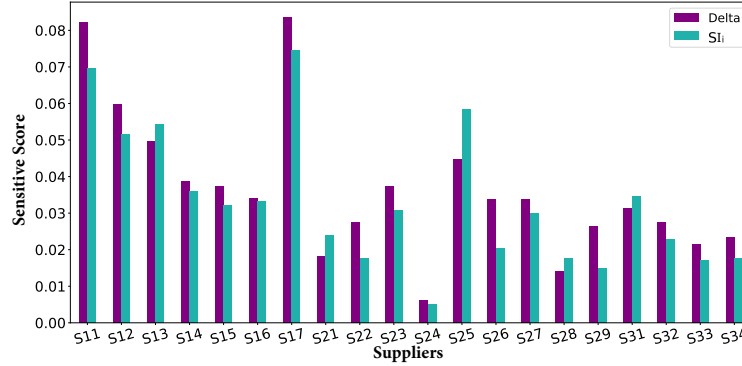


Figure 11: Comparison of sensitivity analysis measures for the focal firm in the case study supply network.

The rankings obtained by the sensitivity measures give the decision-makers directional guidance in which suppliers they must focus their attention and collect information. Mitigation strategies require to be defined for critical suppliers for possessing a high resilience network.

2.7 Conclusion

We proposed an effective framework for resilience assessment within deep-tier supply networks. The framework relies on discrete-event simulation informed by primary and secondary data sources and global supply risk assessment/metric databases for improving resilience assessment. We also demonstrated the importance of deep-tier visibility for an efficient resilience assessment using a case-study informed by a real-world automotive supply network. A supply network has been mapped by considering real-world data with deep tiers transparency and regional risk to enhance the network resilience level's accuracy. We explore the number of lost demands for evaluating our approach and assess the

operational metrics: holding and backorder costs and delivery delays.

The results indicate that the typical approach of considering tier-1 suppliers alone leads decision-makers to overestimate supply network resilience and misjudge operational performance. The results confirm that having deep-tier transparency and regional risk data can improve resilience assessment and can lead to better supply network design or redesign. In the sensitivity-analysis, the most critical suppliers in the network are ranked according to two different sensitivity measures. This provides further direction for the necessity of collecting additional data and allocation of resources within the network.

A potential challenge with the framework is collecting data for supply chain mapping from a public secondary database (IHS MARKIT) and validating it. However, with better processing of data, the proposed assessment framework provides feedback for the state of the supply chain within a firm. This can further help obtain better resilience management techniques. Especially, the recommendations from the framework are essential for practicing managers to evaluate the vulnerability of their supply chain network. Subsequently, requiring better planning strategies to improve their resilience.

CHAPTER 3 RESILIENCE MANAGEMENT FRAMEWORK

3.1 Introduction

The modern supply chains are large-scale and complex systems with hidden vulnerabilities due to the intricacy of supplier interaction, global competition, and escalating customer expectations. Supply chain networks and all their components, such as retailers, manufacturers, suppliers, etc., cope with many unforeseen events. According to McKinsey research, global supply chain shocks with high severity occur more frequently; for instance, the unexpected disruptions with a duration of one month or more happen every 3.7 years, resulting in high financial loss of around 45 percent of one year's company earning [43]. The coronavirus outbreak [3] immediately decelerated the global supply chain flows and activities in 2020 and caused a global shortage of critical parts such as semi-conductors. This shortage created severe anxiety for the majority of firms; for example, automakers had to halt their production in several factories across North America [34]. Other examples are Texas winter storm caused unexpected long shipping delays through the supply network for a couple of months [110]. Japan earthquake and tsunami in March 2011 forced many companies to reduce their production [37], and the explosion at the BASF factory in Germany in 2016 makes the considerable shortage of raw materials in the global supply chain [80].

Globalization and an unstable environment put resiliency on the agenda of every industry's strategy planning step because resilient companies can quickly respond and return to their original state when a disruption event happens. McKinsey survey verified that 93% of supply chain leaders are expected to increase resilience across the supply chains by

considering dual sourcing, increasing inventory level, and nearshoring strategies [4]. The COVID19 pandemic highlighted that boosting the visibility on both the demand and supply chain sides can enable organizations to minimize disruptions while improving productivity [43]. [116] presents that deep-tier visibility plays a critical role in an effective resilience assessment of an automotive supply network. In the research studies, there is a trend of assessing and managing deep-tiers supply chains resilience with defining proper recovery or mitigation strategies [9, 87].

Addressing resilience management from a supply chain point of view is drawing attention from both academics and industries [35, 39, 66, 77, 103, 116]. [118] illustrates that pre-disruption mitigation strategies can be considered to design a resilient supply network and alleviate the negative consequences of disruptions. In addition, supply chains can design contingency strategies to do intended actions after disruption's occurrence [21, 36]. However, many organizations are unable to create proper and dynamic procedures for the post or pre disruption management [39]. In addition, COVID 19 illustrates that a comprehensive view of the supply network through deep tier visibility is crucial to identify hidden risks and mitigate disruption outcomes. McKinsey's research reported that a limited number of large firms cooperate with their tier-1 suppliers to gather the detailed information of large tier-2 suppliers to categorize critical inputs whether they are shipped from high-risk suppliers [79]. In a fast-changing and complex environment, it is time to reimagine resilience management by considering high transparency to minimize the risks with minimal cost.

Numerous methods have been proposed for supply chains resilience management, and they can be categorized into two classes based on quantitative resilience approaches em-

ployed: optimization [48] and simulation [113]. In recent years, the research studies have benefited from the combination of two methods mainly because of its sustainability to address risks. In supply chain resilience management, employing simulation-based optimization can allow business leaders to develop the range of possible scenarios they may face. Furthermore, business leaders can implement stress tests through the deep-tier suppliers' network to ensure their strategies can succeed in a range of future scenarios [119]. However, the implication of simulation-based optimization methods is still scarce in supply chain resilience management, and there are open opportunities to extended this area.

The key contributions of this study include the following: 1) providing a dynamic resilience management framework for deep-tier supply chains; 2) developing a discrete simulation-based optimization leveraged by historical and secondary data sources to assess and optimize the focal firm resilience; 3) introducing an effective surrogate model based on generating regressions model for each tier-1 suppliers, and 4) evaluating the performance of proposed framework by running regular and operating disruption scenarios for tier-1,-2, and -3 suppliers. We validate the framework relying on experiments derived from a real-world dataset from a leading global original equipment manufacturer (OEM). The results demonstrate the critical role of high transparency and deep-tier supply chains visibility on dynamic and efficient resilience management, leading companies to reduce the disruption cost and recovery time. Our framework is general and can be adjusted to various supply networks ranging from pharmaceuticals to electronics and automotive industries, where the goal is to optimize network resilience with affordable cost.

The rest of this study is organized as follows: Section 3.2 reviews the related literature in the scope of supply chain resilience management. Section 3.3 describes the proposed re-

silience management framework. Section 3.4 illustrates the details on the surrogate model to optimize supply chain resilience combined with regression and discrete event simulation with proper disruption settings. Section 3.6 presents results from a real-world case study. Finally, section 3.8 provides some conclusions and directions for future research.

3.2 Literature Review

Resilience is a multi diminutions notation that has been expanded in supply chain management and comes from psychology, social, organizational science and ecology [41, 74, 99]. It refers to a system's capacity to anticipate and recognize unanticipated events and risks before they have a negative impact, and it illustrates how a system can quickly recover to a stable or improved condition when a disruption occurs [131]. [121] summarizes the critical dimensions of supply chain resilience as the timely capacity to plan, respond, and revert to an original or more favorable state. According to some researchers, supply chain resilience is a network-level construct that arises in non-linear and dynamic ways through interacting suppliers' adopting behavior and connections [46, 126]. Resilience can categorize 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 [13]. On the other side, the dynamic perspective is the ability of a system to evolve and move over time to original or improved states [19, 84].

Various supply chain resilience strategies, either proactive, reactive, or both, have been used in the literature to reduce risks and increase efficiency [73]. Contracting with back suppliers, increasing inventory and capacity levels, leveraging openness with information sharing and supplier relationships, and implementing accurate demand forecasting are the

most relevant resilience strategies [45, 53, 63]. 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 [1]. Therefore, the supply chain resilience assessment is critical for leaders to evaluate the current resilience strategies and make future actions or improvements. The resilience triangle has been introduced by [49] to measure the resilience of a system and conducted in supply chain management frameworks. For instance, [133] applied the resilience triangle to quantify resilience for the designed network by defining the nonlinear function to describe the restoration behavior and finally introduced a resilience-based design optimization formulation.

To design/redesign the resilience supply chain, more research studies utilized simulation [42, 88, 105] or analytical models [28, 64, 73] following optimizing techniques. According to supply chain management studies, quantitative and qualitative indicators have been highlighted to design a resilience network. For example, [18] developed a mixed-integer linear model to build a robust network by adding 11 quantitative indicators. [112] proposed 10 qualitative resilience indices to configure a resilience network through the game theory model. In addition to establishing an efficient approach for supply chain resilience management, simulating random and targeted scenarios has been considered by scholars through the optimization model [1, 61, 114]. [45] proposes a comprehensive stochastic optimization to enhance the resilience level of the food supply chain by defining the number of resiliency strategies with generating plausible scenarios to evaluate their model. [5] evaluates multiple resilience strategies to design/redesign the resilience retail supply chain by modeling a stochastic optimization and considering 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 running simulation combined with optimization.

Simulation-based optimization is an appealing combined strategy approach and a valuable tool for decision-makers who wish to determine which combination of parameters and input configurations will result in the optimal system performance [132]. In the recent review paper, [119] highlighted the benefit of employing simulation-based optimization methods in supply chain resilience management. The author listed considering hybrid approached and surrogate models combining with simulation and machine learning as future research opportunities. In addition, [85] presented a unique approach for dealing with supply chain management in the face of demand uncertainty, concentrating on optimizing a large-scale mixed-integer nonlinear problem utilizing discrete event simulation-based optimization. However, there are scarce studies implementing simulation optimization for designing resilience supply networks by running 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 network with minimal cost.

3.3 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 has been used in the proposed framework, shown in Fig.12. The resilience management framework's main steps are as follows: Step 1: Formulate optimization problem, specify the objective function and decision variables related to our network structures, and gain optimal values. Step 2: Generate initial sample points by implementing the Design of Experiment method (DOE) [70, 75]. Step 3: Simulate a deep tier supply chain network to assessing the resilience level for current optimal values from step 1, and all initial sample points are collected from step 2. If the focal firm's resilience level does not satisfy the resilience target, the current mitigation strategies need to be improved, and we go to step 4 to develop the surrogate model. In step 4, the relationship between the value of decision variables (output of step 1) – resilience levels (output of step 3) is created for

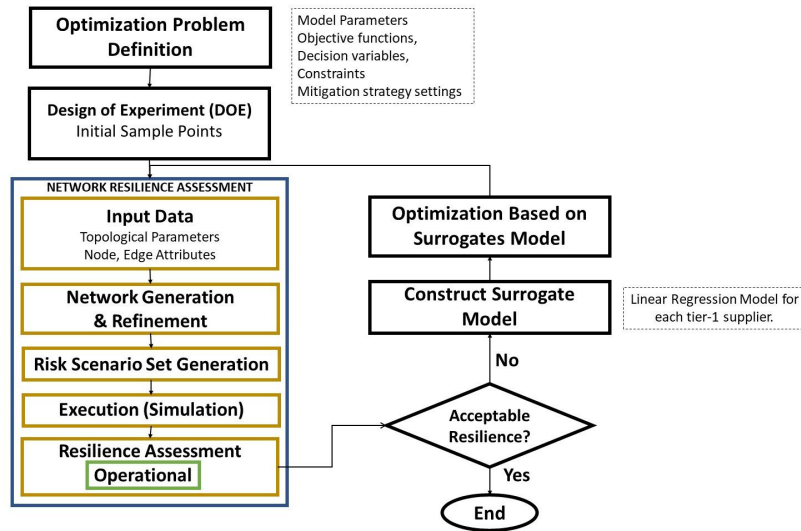


Figure 12: Simulation-based optimization framework

each tier 1 supplier by using a linear regression model (see section 3.5). Step 5: The linear regression models are added to the optimization problem, and then the updated optimization problem is solved. In step 5, we will have new optimal values of decision variables, and we jump to step 3 to assess the resilience level. Finally, these framework steps will be continued till we reach to target resilience level.

3.3.1 Supply chain network

Recent research studies [32, 33, 62, 115] 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. Therefore, 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), three tiers' suppliers, their connections, and related policies following the same networking setting suggested by the study [116]. 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 shipping policies information.

The nature of supply chain resilience management is multi-dimensional and different ways have been provided to measure and assess the impact of short- or long-term disruptions [19, 133]. 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 study, the lost demand (fill rate) frequently cited in the literature has been applied as the performance metric [24, 116]. 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 satisfying 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 R_n for each component can be expressed as follows:

$$R_n(t) = 1 - \frac{LD_n(t)}{TD_n(t)}, \quad \forall n \in N, t \in T. \quad (3.1)$$

$$R_n = \frac{\sum_{t=0}^T R_n(t)}{T}, \quad \forall n \in N. \quad (3.2)$$

3 In the above equations (3.1,3.2) T is the duration of the data collection period and N is Set of nodes for a given supply network. In Eq. 3.1, $LD_n(t)$ and $TD_n(t)$ describe the lost and total demand at supplier n and time period t .

3.3.2 Strategies

Companies and automotive industries usually run the market analysis to determine the potential suppliers and then keep two suppliers offering more competitive unit and tooling costs and quality. Finally, the company will choose one supplier with appealing pricing and quality. In addition, the company can prefer to have single sourcing and sign a contract with one supplier to take advantage of Just In Time (JIT). However, when any disruption occurs in the future, the company will be exposed to the risk of satisfying demand due to single supplier delay delivery or temporarily shutting down. Therefore, the company can opt for different mitigation strategies. The proposed resilience management framework incorporates the following mitigation strategies which enable a resilient network:

- 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 keep extra hold 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 when the primary supplier fails to deliver parts, pre-qualify secondary supplier can cover the backordered as much as its capacity permits. Just secondary supplier needs time to the preparation 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 backordered, the backup supplier can deliver the required parts after preparation.

3.4 Implementation

This section presents details on simulation-based optimization steps to develop a dynamic supply network resilience management in practice.

3.4.1 Optimization Formulation

Based on the proposed framework description in section 3.3, in this section, the mathematical formulation for risk mitigation is developed to minimize total strategy costs of the whole supply chain network. An overview of the notation used throughout the proposed model is present in Table 6.

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

Subject to:

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
 t_k Target inventory level 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 $w_j \leq \psi_k D x_k \leq w_{j+1}$ then $n_{jk} = 1$, otherwise $n_{jk} = 0$.
 o_{kj} A binary variable: if $w_j \leq \psi_k D y_k \leq w_{j+1}$ 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
-

Table 6: Nomenclature

$$x_k + y_k = 1 \quad \forall k \in K \quad (3.3)$$

$$\psi_k D x_k \leq \sum_{j \in J} w_j v_{kj} \quad \forall k \in K \quad (3.4)$$

$$v_{k1} \leq n_{k1} \quad \forall k \in K \quad (3.5)$$

$$v_{kj} \leq n_{kj-1} + n_{kj} \quad \forall k \in K, j \in 2, \dots, J-1 \quad (3.6)$$

$$v_{kJ} \leq n_{kJ-1} \quad \forall k \in K \quad (3.7)$$

$$\sum_{j \in J} v_{kj} = 1 \quad \forall k \in K \quad (3.8)$$

$$\sum_{j \in J} n_{kj} \leq 1 \quad \forall k \in K \quad (3.9)$$

$$\psi_k D y_k \leq \sum_{j \in J} w_j l_{kj} \quad \forall k \in K \quad (3.10)$$

$$l_{K1} \leq o_{K1} \quad \forall k \in K \quad (3.11)$$

$$l_{Kj} \leq o_{kj-1} + o_{kj} \quad \forall k \in K, j \in 2, \dots, J-1 \quad (3.12)$$

$$l_{KJ} \leq o_{KJ-1} \quad \forall k \in K \quad (3.13)$$

$$\sum_{j \in J} l_{kj} = 1 \quad \forall k \in K \quad (3.14)$$

$$\sum_{j \in J} o_{kj} \leq 1 \quad \forall k \in K \quad (3.15)$$

$$e_k \leq 1 \quad \forall k \in K \quad (3.16)$$

$$z_k \leq 1 \quad \forall k \in K \quad (3.17)$$

$$x_k \psi_k D \leq m_k \quad \forall k \in K \quad (3.18)$$

$$y_k \psi_k D \leq g_k e_k \quad \forall k \in K \quad (3.19)$$

$$a_k \psi_k D \leq p_k z_k \quad \forall k \in K, \quad (3.20)$$

$$(3.21)$$

$$s_k > 0 \quad \forall k \in K \quad (3.22)$$

$$x_k, y_k, a_k \in [0, 1]; z_k, e_k, v_{kj}, l_{kj}, n_{kj}, o_{kj} \in \{0, 1\}; s_k \in \mathbb{R} \quad (3.23)$$

The objective function (Eq.3.3) minimizes the total cost is consisted of: reserve capacity at primary and secondary supplier location, 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 3.3 grants a percentage of capacity is reserved as primary or secondary suppliers or both of them. Constraints 3.4-3.15 are related to piece-wise linear reserving capacity at primary suppliers with unit piece price f_{kj} and secondary suppliers with piece price q_{kj} . Constraint 3.16 ensures that at most one secondary supplier is chosen for part k . Similarly, constraint 3.17 makes sure that at most one backup supplier is chosen for the part k . Constraint 3.18 guarantees that the level of regular capacity reserved at the primary supplier does not exceed the maximum capacity level of the primary supplier. Constraints 3.19 and 3.20 ensures that the total amount of reserve capacity from secondary and backup suppliers is not greater than the maximum allowed reserved capacity. Finally, constraints 3.22 and 3.23 represents bounds on decision variables.

The optimization model has been used to find the optimal mitigation strategies for a given supply chain network. Then, this strategic plan will be considered as input for the simulation step to verify the model.

3.4.2 Simulation

In this section, simulation framework is developed to assess the supply network resilience and verify the performance of mitigation strategies (section 3.4.1).

3.4.3 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 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 [70, 75] . We generated 14 initial sample points of decision variables, including primary capacity (x_k), secondary capacity (y_k), backup capacity (z_k), and safety stocks (s_k) for tier-1 suppliers by applying a two-level factorial with center points. We have chosen the initial sample points that satisfy the following conditions:

$$3x_k D + y_k D \geq \lambda_\alpha \psi_k D, \quad \forall k \in K. \quad (3.24)$$

For this study in Equation 3.24, $\alpha = 0.95$, which is equal to network service level and λ_α can obtain by looking at standard normal distribution ($\mathbb{N}(0, 1)$). All initial sample points have been considered as input settings for the deep tier supply network. Then the given network has been 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 point.

3.4.4 Supply Network Simulation

The automotive industry is a complex dynamic network consisting of diversified bill of materials, various nodes with different roles, and diverse connections between them such as material, financing, and information flows. This supply chain network is not easily controllable and predictable in 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 [98, 130], simulation, especially Discrete Event Simulation (DES), is an appropriate method to tackle the complexity and other outstanding issues such as failing to provide the analytical analysis. Thus, the DES model would be the most appropriate approach to 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 [2]. Ultimately, DES can capture the uncertainty and complexity and is well-suited for complex supply chain studies. There are several commercial DES software. We used the Simpy (Python package) [86] because it gives us the flexibility to generate different network structures by integrating with the NetworkX package [91], defining various random disruptions, and designing valuable Performance Indexes dashboard using available Python's features. This study follows the same steps of the current study by [116] for implementing DES simulation through the supply chain network with considering inventory policies, shipment policies, and demand generation for each supplier located in different tiers. All results related to the real case study in the section are obtained from the DES simulation

algorithm using python Packages.

3.5 Surrogate Model

As noted earlier, supply chain resilience management is multi-dimensional in nature, and decision-makers need to optimize all key performance metrics such as capacity utilization, costs, lead times, service levels, and so on. 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 2: Surrogate Model

- 1 **Step 1:** Define the initial optimization formulation refer to Equations 3.3-3.23 and solve the model.
 - 2 **Step 2:** Run network simulation (see section 3.4.4) for initial sample points and optimal values of decision variables to estimate the resilience (section 3.3.1) of each tier-1 supplier.
 - 3 **Step 3:** Generate the regression models based on simulation results (see section 3.5.1) for each tier-1 supplier.
 - 4 **Step 3:** Add new/updated constraints to initial optimization formulation (Equations 3.26-3.29).
 - 5 **Step 4:** Solve the updated optimization problem and obtain the optimal values of decision variables.
 - 6 **Step 5:** Run network simulation for new optimal value of decision variables and estimate the resilience levels.
 - 7 **If** $R_f = \bar{R}_F$:
 - 8 the optimal mitigation strategies for each tier-1 supplier has been defined.
 - 9 **Else** Move step 3.
-

3.5.1 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) has been 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: $X_k = x_k * D * \psi_k, Y_k = y_k * D * \psi_k, Z_k = z_k * D * \psi_k, s_k$. The goal here is to maximize the

values of focal firm resilience with considering its multi-dimensional nature such as minimizing cost or delay delivery. We can update the our optimization problem as following:

1) Regression: generate a linear relationship between resilience levels and other independent variables. The linear regression is employed for modeling, the result is:

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

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

2) Optimization:

Our dependent and independent variables are (mostly) continuous and we have $k + 1$ dependent variables. Our primary interest is minimizing cost, while satisfying value of R_F and $R_k, k \in K$ to reach the target focal resilience level \bar{R}_F (Eq. 3.2).

$$\text{Min Cost} \quad (\text{Eq. 3.3}) \quad (3.25)$$

$$R_F \geq \bar{R}_F \quad (3.26)$$

$$|R_F - (\gamma_0 + \gamma_1 R_1 + \gamma_2 R_2 + \dots + \gamma_k R_k)| \leq \theta \hat{\sigma}_{\epsilon_{R_F}} \quad (3.27)$$

$$|R_k - (\beta_0 + \beta_1 x_k + \beta_2 y_k + \beta_3 z_k + \beta_4 I_k)| \leq \theta \hat{\sigma}_{\epsilon_{R_k}} \quad \forall k \in K \quad (3.28)$$

$$R_F, R_k \in \mathbb{R}^+ \quad (3.29)$$

The accuracy and robustness of the results rely on how the regression models are perfect with high accuracy. Since the regression models are not guaranteed to be perfect, we added slacks to our regression models to cover the imperfection. The slack defines as $\theta * \sigma$, where σ represents the regression model standard error, and a smaller value of θ will create the strict constraints. Finally, Equations 3.2 - 3.29 will be added to optimization model.

3.6 Results & Managerial Implications

3.6.1 Automotive Supply Network Setting

We demonstrate the capability of the proposed deep tier resilience management framework on a real supply network for an automotive climate control sub-system. A tier-3 supply chain network belonging to a global automotive original equipment manufacturer (OEM) located in North America has been designed. The network consists of different suppliers located in various locations with different regional risk Indexes (for details, refer to Table 7). In Table 7, regional risk indexes are obtained from the IHS Markit website [57], a distinguished secondary database. Daily production volume related to the final assembly plant 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.

| 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

Table 7: Location with IHS Markit's unique country risk. (Source: IHS Markit 2020; Updated Q2-2020)

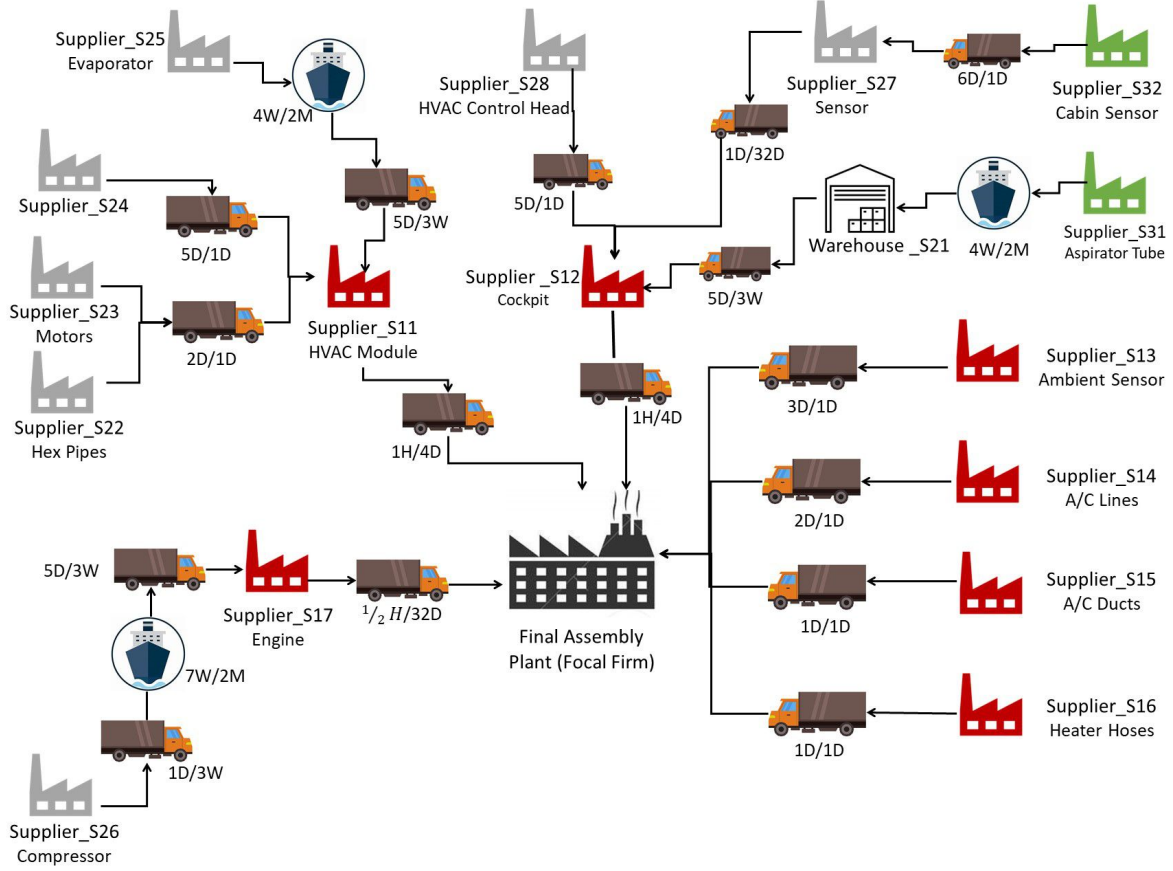


Figure 13: Case study supply network for an automotive climate control system.

H: hours, D: days, W: weeks, M: months.

On Fig. 13 shipping information including shipping mode, duration, and frequency between suppliers in different tiers, tier-1 suppliers and final assembly plant has been determined. 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 happened every two months with seven weeks delivery duration. Part names for each supplier reveal in Fig. 4; 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 setting suggested in the study by [116]. 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 a key performance function to assess the resilience level of the focal firm and all suppliers during the simulation.

3.6.2 Simulation Settings

As noted in section 3.4.4, 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 wrap-up of 90 days and 10-time replications. During the simulation, regular disruption frequency and intensity are estimated according to risk index (for details, refer [116]), and all expected performance metrics and resilience level (section 3.3.1) 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 Intel Corei5-6300U CPU (2.4 GHz) with 8.00 GB RAM has been used for running the proposed simulation-based optimization. In the following subsections, we discuss the results of optimal mitigation strategies to reach the given target

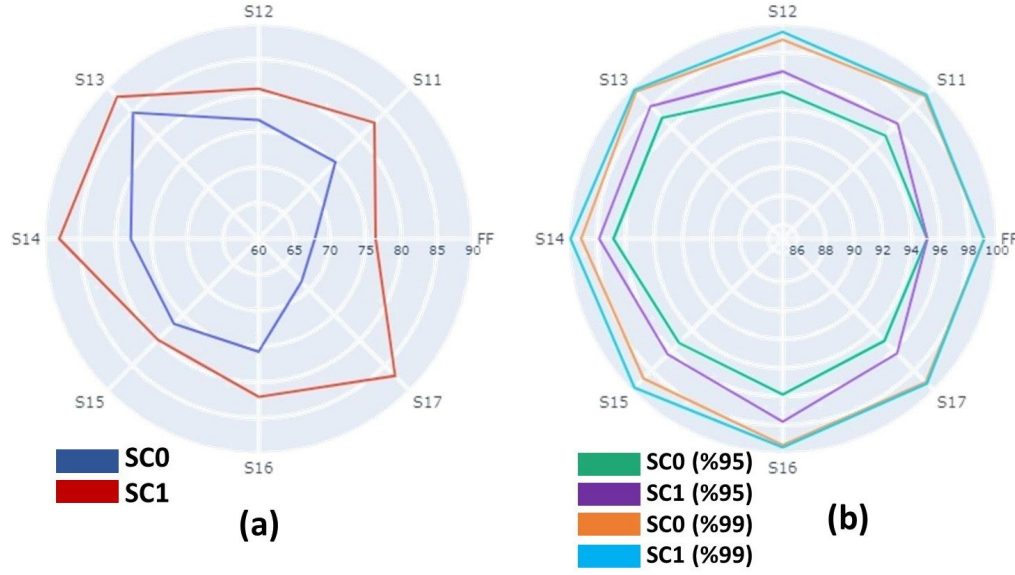


Figure 14: Estimated node resilience for focal firm (FF) and tier-1 suppliers under different levels of upstream visibility and different resilience target level [Full Visibility Scenario (SC0), Typical Scenario (SC1)]

resilience levels for different levels of visibility with a brief discussion of significant managerial insights obtained from our study.

3.6.3 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 14 compares two levels of visibility under three different target resilience levels. The results confirm that there is an overestimation of resilience in all scenarios when the supply chain network focuses on tier-1 suppliers. Moreover, the resilience overestimation is very tangible (Fig.14a) when decision-makers do not set any resilience level and consider any mitigation strategies. However, our resilience management framework can reduce this gap but still, this overestimation of resilience levels could not be ignorable, and

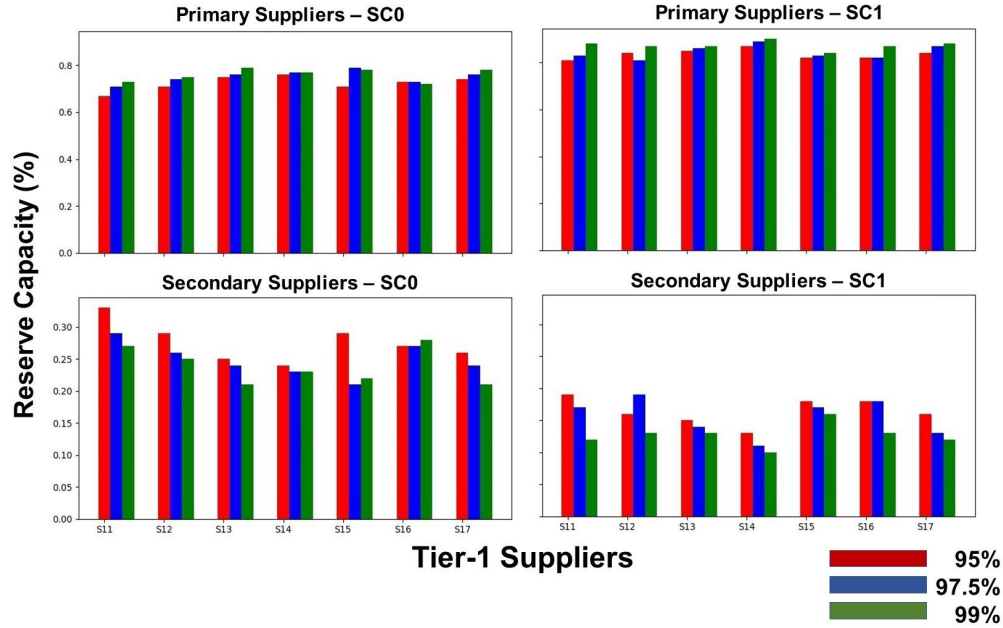


Figure 15: Optimal reserve capacity level at primary and backup suppliers for different resilience target level [Full Visibility Scenario (SC0), Typical Scenario (SC1)]

Fig.14.b verifies the indigence of considering extra information and deep-tier visibility to reach the expected resilience in all tier-1 suppliers and focal firms. In addition, Fig.14.b compares the resilience levels of tier-1 suppliers and focal firms when the focal firm 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 this high tightness for tier 1 suppliers in %95 scenarios. For instance, in the %99 target resilience level, 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 satisfied 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.15 reports the level of reserve 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 reserve capacity at primary suppliers when the supply chain network has limited visibility on the tier-1 suppliers. However, in another scenario with posing visibility and transparency beyond tier-1 suppliers, the resilience management framework suggests more reserve capacity on the secondary supplier location to reach the expected resilience level. Fig.15 highlights that when the supply chain network is looking for a higher resilience level, the optimal mitigation strategy offers more reserve capacity levels in primary suppliers in comparison to secondary suppliers, which can be because of considering the trade-off cost - resilience level. In the following section 3.7 other performance indexes (KPIs) will discuss under different target levels to find how the proposed framework can be effective and efficient.

3.7 Supply Cost and Responsiveness Assessment

Fig.16 plots the holding and backordered costs under three mitigation plans scenarios: 1. no mitigation strategies, 2. consider %95 target resilience level, 3. consider %99 target resilience level. For the length of simulation (around three years), the resilience management framework can improve the lost demand 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 cost, for instance, in average %33 and %41 reductions when supply network moves from no mitigation strategies to considering %95 and %99 targeted resilience level, respectively. In addition, we can

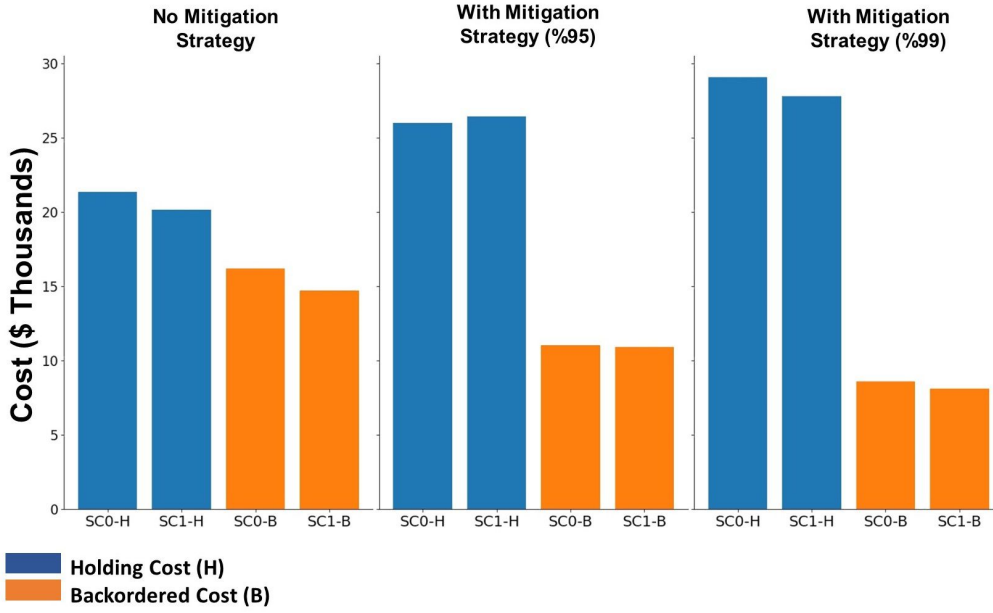


Figure 16: Estimated total holding and back-ordered cost for focal firm under different levels of deep-tier visibility and target resilience level [Full Visibility Scenario (SC0), Typical Scenario (SC1)]

see the same and consistent behavior under different visibility scenarios, which can prove that the proposed framework is efficient. There is a minor increase in backorder costs compared to full visibility of the supply network (SC0) with limited or typical visibility levels.

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.17 reports the distribution of order shipment delays of suppliers tier-1 under two categories (without mitigation strategies and with mitigation strategies reaching to %99 resilience target 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 delays delivery to focal firms under full (SC0) and limited (SC1) visibility scenarios, respectively. On the other side, proposed resilience management optimizes the mitigation

strategies to reach the %99 resilience level the supplier S_{11} poses the maximum 4 and 3 days delays delivery 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.

3.7.1 Optimal Resilience Strategies for different slacks setting

As noted in section 3.5.1 regarding adding slacks (θ) to cover the imperfection of regression models, Table 3.7.1 reports detailed results under various slacks values when the supply chain network poses the full visibility with %97.5 target resilience level. The estimated tier-1 suppliers' resilience levels, holding cost, backordered, primary and secondary reserved capacity levels with inventory level have been compared, and it demonstrates

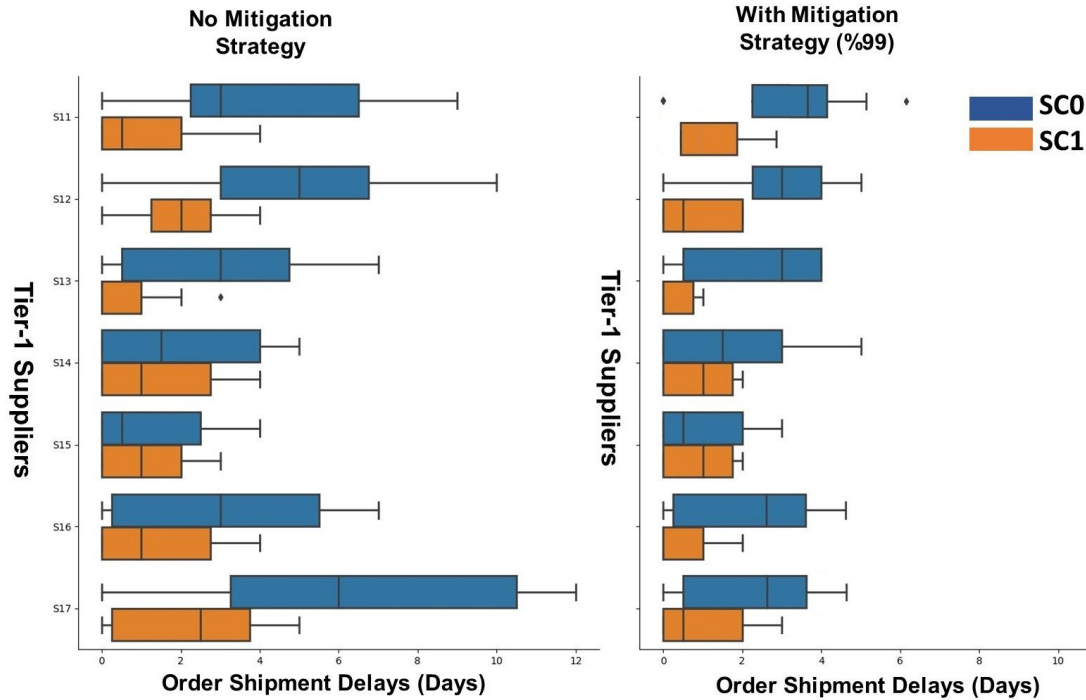


Figure 17: Estimated order shipment delays by tier-1 suppliers under two different visibility scenarios and mitigation strategies [Full Visibility Scenario (SC0), Typical Scenario (SC1)]

| | $\theta=2$ | $\theta=0$ | $\theta=1$ | $\theta=3$ |
|------------------------------------|------------|------------|------------|------------|
| 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.3.1-3.2

Table 8: Comparison proposed framework with different slack values for generate regression function under target level %97.5

more tightened behavior for supply chain network when $\theta = 0$ (minimum values). For instance, in $\theta = 0$ the costs and variance of suppliers' resilience level are lower in comparison to $\theta = 2$ or 3. Also, the proposed prove the constancy behavior under different simulation settings ($\theta=0,1,2$, and 3), and just negligible increase can be seen in costs and inventory levels when θ 's value has been changed from 0 to 1.

3.8 Conclusion

The supply chain network must design or redesign more resilient in the face of an uncertain environment with more frequent or severe disruptions. The automotive industry is a complex and vulnerable supply chain network due to globalization and a lack of transparency beyond tier 1 suppliers, which increases the supply chain's exposure when one of the suppliers in the network shutdowns for a couple of weeks. Therefore, developing 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 research study was designed to develop 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 deep-tier supplier's connection 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 supplier will be fragile and vulnerable in the face of disruptions. The framework and tests reflect the real risk that OEMs 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 backup capacity with a primary supplier, reserving capacity from a secondary supplier, contracting with a backup supplier, and creating initial inventory have been considered. Due to the multidimensional nature of the supply chain resilience network, 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 capacity while facing random and low severity disruption and moving to utilize 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 is facing severe disruption with a high value of recovery duration through the network. However, providing the proper mitigation strategies by considering a high level of visibility can alleviate the consequence of extreme disruptions.

Potential future research is considering the effect of supply chain structures of different industries on the recovery and mitigation strategies. It means how this dynamic resilience management can be compatible with other industries such as electronics with different structures and risk profiles, and how they can benefit by implementing this framework. Other future research directions can be modeling stochastic and risk-averse formulation to consider more scenarios and validate the framework while considering worse case scenarios or other uncertainty such as demand disruption.

CHAPTER 4 CONCLUSION & FUTURE RESEARCH

4.1 Conclusion

Globalization, combined with growing market and environmental risks/uncertainties, is forcing companies across industries to design more resilient supply networks. The COVID-19 pandemic and the semiconductor chip shortage problems of 2021 have clearly demonstrated that global supply chains are not resilient and quite vulnerable to all sorts of natural disasters and man-made disruptions. As for academic literature, most of the suggested frameworks for network resilience management either lack practical utility or incomplete (e.g., by limiting the focus to just immediate suppliers). There is strong evidence that over 50% of the risks to firms stem from deeper tiers of the supply network. To address these issues, we developed an effective resilience assessment and management framework for complex deep-tier supply networks. In the absence of deep-tier visibility, our research demonstrates that firms are likely to overestimate network resilience and fail to manage them effectively.

The proposed resilience assessment methodology consists of four modules: 1) Mapping the supply chain network and setting related parameters/policies; 2) Generating (routine and rare-event) disruption scenarios; 3) Simulating the network; and 4) Conducting resilience assessment considering multi-dimensional performance metrics. Discrete-event simulation has been chosen as the primary method to simulate supply networks. For generating disruption events and define related parameters such as severity and frequency, we utilized the regional risk indexes by looking at public secondary data sources. Given that most Western firms lack deep-tier supply network visibility due to arms length rela-

tionships with most suppliers (unlike Japanese firms such as Toyota), the growing list of secondary data sources from firms such as Marklines and IHS Markit can help alleviate this problem for mapping the deep-tier networks during assessment. We implemented the proposed framework by integrating two python packages, NetworkX for tracking the network connections and structures and SimPy for programmatically implementing discrete-event simulation models and tracking resilience metrics. Our experiments informed by a real-world automotive case study demonstrate the effectiveness of the proposed supply network resilience assessment methodology.

We also propose an effective resilience management framework that efficiently leverages simulation-based optimization. For illustrative purposes, we considered the mitigation strategies typical in the automotive industry, such as dual sourcing, reserve capacities (at primary or secondary suppliers), and contracts with backup suppliers besides carrying safety stock. Sourcing and transportation mode decisions can be easily incorporated into the framework. The method seeks to minimize the cost of risk mitigation strategies while attaining the target resilience. The framework is flexible and can entertain other objectives and constraints. Given that simulation-based optimization methods can be computationally expensive, we employ surrogate models that relate supply network resilience performance to network design parameters within our mathematical programming formulation. Without loss of generality, the surrogate models are based on linear regression models that define the relationship between focal firm and tier-1 suppliers' resilience levels and network design decision variables. The imperfections of the regression models are accounted for in the formulation through constraints with slack (function of the RMSE of the regression model). We demonstrate that optimal resilience management would stem

from jointly allocating safety buffers (e.g., capacity, inventory levels) across the network and not by independently applying a simplistic/static set of rules for all nodes/arcs. Our validation experiments with a real-world case study informed by secondary data from public data sources confirm the effectiveness and efficiency of the proposed supply network resilience management method.

4.2 Future research

There are several avenues for future research. First and foremost, the proposed methodology should be tested and refined with additional automotive case studies across geographical regions. The proposed methodology is general and should prove to be useful for other industries as well. A potential future research extension is adding the impact of firm-level risk heterogeneity factors like financial performance, inadequate manufacturing or processing capability, low-process stability, and changes in technology within the primary regional risk indices to the proposed deep-tier resilience assessment framework. As noted earlier, most Western firms lack deep-tier supply network visibility due to arms length relationships with their immediate suppliers. Given this, the suppliers are generally unwilling to share much information about their own suppliers for lack of trust. To overcome this difficulty, future research can explore the possibility of developing resilience “adjustment factors” based on the type of commodity and/or supply network structure, while limiting the resilience assessment to just tier-1 suppliers. There are also opportunities to improve the proposed sensitivity analysis methods for identifying critical suppliers and network operation policies.

The efficiency of the proposed resilience management methodology can be improved

by improving the surrogate model accuracy for the simulation-based optimization framework by incorporating supply network structure parameters into the regression model or incorporating nonlinear regression functions. Finally, future research can explore modeling stochastic and risk-averse formulations to consider more scenarios and validate the framework while considering worst-case scenarios or additional uncertainty around both supply and demand disruptions.

APPENDIX A

Case Study Network Attributes & Parameters

Inventory policy parameters and transportation lead-times employed for the case study supply network:

- Target service level for inventory management at all supply network nodes is assumed to be $\beta = 0.95$ (i.e., 95%).
- Holding cost rate is assumed to be 0.041% of unit price per day. Holding cost = Piece price ($\$/US/Unit$) \times Finished good inventory ($Units/Day$) $\times 0.00041$.
- Initial inventory at the start of the simulation is assumed to be adequate to cover two weeks of demand.
- Profit margin is considered to be the same as the back-order cost.
- Shipment lead-time is assumed to be $\frac{m_{nj} \times c}{s \times h}$, where m_{nj} is the Haversine distance between two nodes (miles), s denotes transportation speed (mph), h denotes daily transportation operation hours, and c denotes the distance correction multiplier. The settings for these parameters based on transportation mode are reported in Table 9.
- Haversine distance between two nodes can be obtained as follows: $m_{nj} = 2r \arcsin(\sqrt{\sin^2(\frac{\phi_j - \phi_n}{2}) + \cos(\phi_n)\cos(\phi_j)\sin^2(\frac{\lambda_j - \lambda_n}{2})}$, where $\phi_n, \phi_j, \lambda_n, \lambda_j$, and r represent latitudes of points n and j , longitudes of points n and j , and radius of the sphere, respectively.
- Safety Stock = $Z_\beta \times \sqrt{\mu_D^2 \times \sigma_{LT}^2 + \mu_{LT} \times \sigma_D^2}$, where $\mu_D, \sigma_D^2, \mu_{LT}$, and σ_{LT}^2 represent mean and standard deviation of demand and lead-time, respectively.

- Shipment capacity can set according to shipment mode, part weight (lb./Unit) and piece volume ($ft^3/Unit$).

| Mode | Speed (mph): <i>s</i> | Daily Hours: <i>h</i> | Distance Correction Multiplier: <i>c</i> |
|--------------|-------------------------------------|-------------------------------------|---|
| Truck | 45 | 11 | 1.25 |
| Rail | 60 | 18 | 1.25 |
| Boat | 20 | 23 | 1.1 |
| Air | 180 | 24 | 1 |
| Other | 100 | 24 | 1 |

Table 9: Parameters employed for obtaining order shipment lead-times.

Node attributes including node name, longitude, latitude, region, risk index, and initial inventory are listed in Table 10. Edge attributes including source ID, target ID, shipment mode, shipment capacity, review period, lead-time, and safety stock are listed in Table 11.

| Name | Latitude | Longitude | Region | RiskIndex | Piece Weight (<i>lb/Unit</i>) | Piece Volume (<i>ft³/Unit</i>) |
|------------|------------|--------------|--------|-----------|------------------------------------|--|
| Focal Firm | 29.0745 | -110.95944 | MX | 2.7 | NA | NA |
| S11 | 27.0745 | -109.95944 | MX | 2.7 | 50 | 4 |
| S12 | 26.0745 | -108.95944 | MX | 2.7 | 0.18 | 0.6 |
| S13 | 30.2246036 | -95.2469095 | USA | 1.6 | 8.23 | 1.25 |
| S14 | 20.84266 | -99.848149 | MX | 2.7 | 12 | 0.04 |
| S15 | 25.4217215 | -101.0001139 | MX | 2.7 | 8.23 | 2.35 |
| S16 | 25.5946939 | -103.400692 | MX | 2.7 | 8.23 | 1.25 |
| S17 | 29.0892 | -110.9613 | MX | 2.7 | 8.23 | 1.25 |
| S21 | 19.048599 | -98.192902 | MX | 2.7 | 0.72 | 0.75 |
| S22 | 25.42139 | -101.00024 | MX | 2.7 | 8.23 | 2.35 |
| S23 | 41.003929 | -89.134003 | USA | 1.6 | 8.23 | 1.25 |
| S24 | 41.666515 | -87.557064 | USA | 1.6 | 7.34 | 0.03 |
| S25 | 27.560001 | -110.54467 | MX | 2.7 | 0.72 | 0.75 |
| S26 | 35.1049 | 129.0713 | KS | 1.5 | 12 | 0.04 |
| S27 | 20.011199 | -98.192922 | MX | 2.7 | 8.23 | 2.35 |
| S28 | 35.7307088 | -78.6291299 | USA | 1.6 | 7.34 | 0.03 |
| S29 | 20.9636 | -97.4045 | MX | 2.7 | 12 | 0.04 |
| S31 | 53.4437216 | 27.9705154 | BR | 2.5 | 0.72 | 0.75 |
| S32 | 41.268116 | -80.798241 | USA | 1.6 | 7.34 | 0.03 |
| S33 | 35.89169 | 128.63075 | KS | 1.5 | 12 | 0.04 |
| S34 | 49.69473 | 4.8759 | FR | 1.7 | 0.72 | 0.75 |

Table 10: Node attributes for supply network case study.

| Source ID | Target ID | Shipment Mode | Shipment Capacity (units) | Review Period (days) | Lead Time (days) | Safety Stock (units) |
|-----------|------------|---------------|---------------------------|----------------------|------------------|----------------------|
| S11 | Focal Firm | Truck | 880 | 1 | 1 | 210 |
| S12 | Focal Firm | Truck | 6480 | 1 | 2 | 310 |
| S17 | Focal Firm | Truck | 3110 | 1 | 0 | 200 |
| S13 | Focal Firm | Truck | 3110 | 2 | 3 | 121 |
| S14 | Focal Firm | Truck | 3666 | 3 | 4 | 114 |
| S15 | Focal Firm | Truck | 1654 | 3 | 1 | 670 |
| S16 | Focal Firm | Truck | 3110 | 3 | 1 | 480 |
| S22 | S11 | Truck | 1654 | 1 | 4 | 630 |
| S23 | S11 | Truck | 3110 | 1 | 3 | 688 |
| S24 | S11 | Truck | 5994 | 1 | 2 | 774 |
| S25 | S11 | Truck | 5184 | 4 | 1 | 200 |
| S27 | S12 | Truck | 1654 | 2 | 3 | 940 |
| S21 | S12 | Truck | 5184 | 1 | 5 | 1050 |
| S28 | S12 | Truck | 5994 | 4 | 7 | 1077 |
| S29 | S17 | Truck | 3666 | 1 | 2 | 1350 |
| S26 | S29 | Boat | 3666 | 1 | 28 | 6636 |
| S31 | S21 | Boat | 5589 | 4 | 16 | 4966 |
| S33 | S26 | Truck | 3666 | 4 | 0 | 400 |
| S32 | S27 | Truck | 5994 | 3 | 15 | 948 |
| S34 | S25 | Boat | 5589 | 4 | 10 | 3953 |

Table 11: Edge attributes for supply network case study.

APPENDIX B

Simulation Setting & Python Packages

In this dissertation, for running discrete-event simulation - optimization models, we relied on several powerful Python packages. Fig.18 illustrates the overall structure and related information connection between each module. The Python packages and their structure give us a lot of flexibility in simulating complex supply networks and optimizing the strategies options. The structure includes five Python packages and eight modules. A brief description of these modules and packages is as follows:

- NetworkX package [91] gives us the ability to map the supply network and create related connections. We could easily record and update the node and edge at-

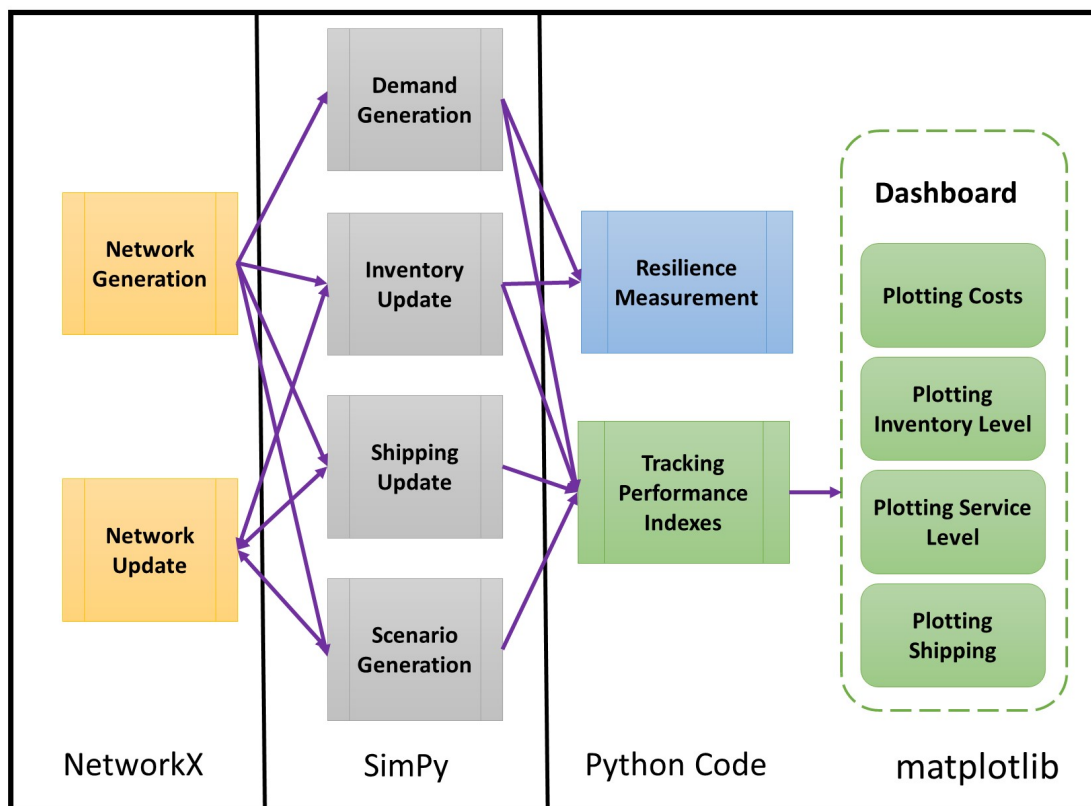


Figure 18: Discrete Event Simulation - Optimization Structure & Packages

tributes/measures by using NetworkX features. In addition, time as a new feature has been added for integrating the NetworkX and the SimPy sections.

- SimPy Package [86] is a powerful Python package to run discrete-event simulation. We have four modules, including inventory, demand, shipping updates, and scenario generation, where the SimPy features have been adjusted to run discrete-event simulation.
- There are several connections between NetworkX and SimPy packages to ensure the network structure, related attributes, and other information would be updated based on the current status in SimPy packages. These connections with their arrows are demonstrated in Fig.18.
- All information and updated data have been recorded in various Excel files. These Excel files with given structures have been moved between modules.
- the docplex package [23] is known as a Python modeling library for optimization and mathematical algorithm. By utilizing this package, we formulate and optimize our resilience management problem. The optimized decision variables have been considered as input for network simulation running by SimPy Package.
- In our framework, we utilize the SciPy package [108] to generate the initial sample by running the design of the experiment method. In addition, this package gives us the ability to generate statistical reports of simulation outputs.
- Finally, we have simulation output (Excel Files) for different scenarios and parameter settings. We employed the matplotlib [56] package to plot and create a dashboard.

The Python code structure and modules can be used for different supply networks with different policies and limitations. Our simulation models can be adjusted for various industries through simple changes in input Excel files such as node/edge attributes and related policies. The Python codes and related packages are available on GitHub website at following address:

<https://github.com/elhamtgh/NetworkX-Supply-Chain-Simulation>

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ABSTRACT**FRAMEWORK FOR EFFECTIVE RESILIENCE MANAGEMENT
OF COMPLEX SUPPLY NETWORKS**

by

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In today's environment with highly global and complex supply chains for engineered products, the ability to assess and manage the resilience of supply chains is not a luxury but a fundamental prerequisite for business continuity and success. This is particularly true for firms with deep-tier supply chains, such as the automotive original equipment manufacturers (OEMs) and their suppliers. Automotive supply networks are particularly facing growing challenges due to their complexity, globalization, economic volatility, rapidly changing technologies, regulations, and environmental/political shocks. These risks and challenges can disrupt and halt operations in any section of the supply network. Given that supply chains have become quite lean in the 21st century with relatively little slack, the COVID-19 pandemic has fully exposed these vulnerabilities. According to Allianz's Business Risk Report from 2014, half of all supply chain disruptions stem from tier-2 and tier-3 suppliers. However, the industry's supply network assessment practice is primarily limited to immediate (i.e., "tier-1") suppliers with no real consideration for the deep-tiers. The added complication due to poor supplier relations is that there is no visibility to the

upstream deeper-tiers of the supply network, which could lead to severe vulnerabilities and impose massive disruption costs.

Our research goal is to enhance the resilience of deep-tier automotive supply networks through improved resilience assessment and management mechanisms. In this collaborative study with a global automotive OEM (Ford Motor Company), we seek to develop methods to assess and manage the resilience of deep-tier supply networks. This research considers the multi-dimensional nature of resilience management focusing on metrics around cost efficiency, effective inventory management, demand fulfillment, capacity management, and delivery performance. We develop and evaluate our proposed resilience assessment and management framework with a real case study supply network for an automotive climate control system. The supply network contains 20 firms (nodes) located in various global regions and 21 connections (edges) between firms. The network contains three-tiers of suppliers with different transportation modes, making the network a rich illustrative example for proposed resilience assessment and management methods and analysis. All inventory and shipping policies with related parameters have been defined and set for each supplier and their connections.

The proposed resilience assessment framework relies on discrete-event simulation for effectiveness; computational efficiency is maintained by relying on modern open-source packages for modeling, optimization, and analysis. The framework starts by generating a digital model of the supply network that includes the focal firm and its suppliers and deeper-tiers based on the available visibility. Disruption scenarios, including disruption sources, frequency and severity, are then efficiently generated using private and public regional risk sources. For illustrative purposes, we primarily relied on public secondary data

sources. The secondary regional risk indices that we relied upon aggregate political, economic, legal, operational, and security risks for the given region. Finally, the digital supply network is simulated with adequate number of replications for reliable assessment. In this research, discrete-event simulation is implemented using NetworkX and SimPy Python packages. We employ the network analysis techniques combined with discrete-event simulation informed by secondary data sources for improving the assessment framework. Our resilience assessment results confirm that visibility into the deeper-tiers of the supply network (through primary or secondary data sources) leads to more accurate network resilience assessment. Finally, we offer a global sensitivity analysis procedure to determine the supply network players, parameters and policies that most influence the network performance.

We also propose an effective resilience management framework that efficiently leverages simulation-based optimization. For illustrative purposes, we considered the mitigation strategies typical in the automotive industry, such as dual sourcing, reserve capacities (at primary or secondary suppliers), and contracts with backup suppliers besides carrying safety stock. Sourcing and transportation mode decisions can be easily incorporated into the framework. The method seeks to minimize the cost of risk mitigation strategies while attaining the target resilience. The framework is flexible and can entertain other objectives and constraints. Given that simulation-based optimization methods can be computationally expensive, we employ surrogate models that relate supply network resilience performance to network design parameters within our mathematical programming formulation. Without loss of generality, the surrogate models are based on linear regression models that define the relationship between focal firm and tier-1 suppliers' resilience lev-

els and network design decision variables. The imperfections of the regression models are accounted for in the formulation through constraints with slack (function of the RMSE of the regression model). We demonstrate that optimal resilience management would stem from jointly allocating safety buffers (e.g., capacity, inventory levels) across the network and not by independently applying a simplistic/static set of rules for all nodes/arcs. Our validation experiments with a real-world case study informed by secondary data from public data sources confirm the effectiveness and efficiency of the proposed supply network resilience management method.

AUTOBIOGRAPHICAL STATEMENT

Elham Taghizadeh received her B.S. and M.S. degree in industrial engineering from K. N. Toosi University of Technology, Tehran, Iran, in 2010 and 2012, respectively. In 2016, she joined the Department of Industrial & Systems Engineering at Wayne State University for her Ph.D. degree under the supervision of Dr. Ratna Babu Chinnam and Dr. Saravanan Venkatachalam. Her research interests are in Supply Chain Management, Machine Learning, Predictive Analysis, Applied Operations Research, and Operation Management.

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