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Mathematical Programming Approach to Optimize Tactical and Operational Supply Chain Decisions under Disruptions

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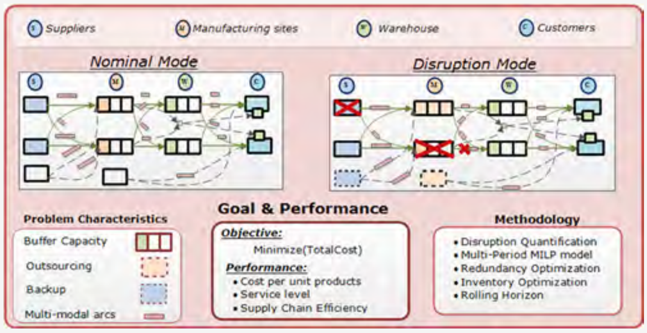
ABSTRACT: Supply chain (SC) networks have become more prominent, complex, and challenging to manage, especially considering the multitude of risks and uncertainty that may manifest. Studies have shown two basic approaches to hedge against the negative impact of SC disruptions: proactive and reactive. While the former methods suggest different approaches to generating robust and resilient structures, the latter approach ensures that the SC recovers effectively. A general shortcoming of existing work is not considering SC dynamics. Consequently, disruptions are considered static events without including the durations and recovery policies. In this work, we develop a SC model that aids decision-making in addressing disruptions by considering proactive and reactive strategies. We adopted a discrete time-expanded model to solve the SC problem and consider the disruption dynamics using the rolling horizon framework. In the proposed SC model, a graph network represents the SC, where the nodes consisting of suppliers, manufacturing sites, warehouses, and customers interact using the arcs. The arcs determine the flow of materials between nodes. Independent disruptions can occur at the nodes and/or arcs, and the time of disruption is quantified using the geometric distribution. In the advent of disruption, we have adopted adjusting routing plans, inventory levels, capacity flexibility, and other tactical and operational decisions to hedge against disruption. To illustrate the proposed approach, we used a small problem to illustrate the effect of arcs and node disruption in decision-making and a realistic case study to demonstrate the proposed framework's computational complexity. The results suggested that the effect of node disruption is more predominant because the initial network configuration limits the flexibility at the nodes. Furthermore, it was shown that the SC operated efficiently, as the solution offers a balance between the service level and the total cost of operating the SC.



1. INTRODUCTION

In today's competitive and uncertain business environment, companies are increasingly exposed to various uncertainties in the supply chain (SC), including disruptions. As such, disruption consideration is a call for concern within the SC community.[1,2] In April 2021, a combination of weather and underestimated fluid dynamic forces caused a giant supercargo to wedged sideways in the Suez Canal, bottling up a critical global trade route; a month later, a cyberattack shut down the operations of a major gas pipeline along the east coast of the United States, and earlier in February, a rare deep freeze and power outage in Texas disrupted some petrochemical plants, creating a shortage of key plastics and resins for a range of industries. To mention a few, these events indicate the importance of considering disruptions while making SC decisions. Amidst these disruptions, the enterprise's survival hinges on achieving a strategic fit. A strategic fit ensures a balance between the different enterprises' objectives. Broadly speaking, these objectives are classified under three broad classes: cost minimization, service level maximization, and inventory policy optimization. Thus maintaining a strategic fit is exploiting the interdependencies between these objectives.[3,4] The strategic fit requires an understanding of SC mitigation and contingency options to handle the disruption in the event of its occurrence and integrate these options into SC drivers within the enterprise to support a more responsive SC.[4]

The nature of the global market has been forcing the enterprise to expand its SC network, consequently making the structure more complex. The higher complexity of the SC network makes it more vulnerable than ever to various threats in the form of risks and uncertainties. These threats are disruptive or operational events. Works of literature have addressed operational uncertainties;[5−8] such uncertainties are due to supply−demand coordination events and may result

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from inadequate coordination between SC entities, thus leading to imperfect information and failed processes. Disruption uncertainties result from man-made/natural disasters, pandemics, or strikes. Such disruptions are external to the SC network and deform an existing SC topology.[9,10] To ensure that the SC achieves a strategic fit, a new SC network should be designed to be resilient or fortify an existing network to make it more reliable.[11] Many authors have proposed practical approaches to achieve a strategic fit in case of disruptions.[9−14] The overall goal is to adapt to evolving supply/demand at the tactical and operational levels and manage uncertainty by boosting flexibility and capacity.[15] Some of the strategies to achieve the strategic fits are (i) making the SC more flexible by expanding capacities and increasing supplier options; (ii) enhancing collaborations between SC entities by sharing information to improve forecasts and using clients' locations to store extra inventory; and (iii) improving the network's agility by introducing product commonality and adding holding reserve inventory. To achieve the aims above, studies have explored different options. Some include ensuring resilient supplier selection, reliable facility (manufacturing sites and warehouse) locations; flexible facility options; and refined predictions of the exogenous parameters (such as raw material price, quality, product price, and demand forecasts) that affect the SC network.

Additionally, studies have explored interactions between strategic fit enhancers. They have noted that SC flexibility represents internally focused manufacturers' capabilities and responsiveness in a firm's internal functions, while SC agility represents externally focused manufacturers' competencies that emphasize speed at the organizational level.[16,17] Combining flexibility and agility ensures better SC responsiveness. Moreover, collaborations between the SC entities reduce uncertainties, which results in more accurate decision-making, and the redundancy strategy adds to the robustness of decisions improving the available options of the entire network.[18] To achieve a high customer service level at a low cost, a variety of complex, interconnected decision-making problems needs to be solved. The decision-making problems are strictly associated with the control and optimization of materials (as well as financial and information flows) in the SC network, in particular, the optimization of disrupted flows. Going forward, disruption in this work is defined as the breakdown of a SC entity. Entities include suppliers, manufacturers, warehouses, customers, and the transportation modes connecting them. The suppliers, manufacturers, warehouses, and customers are generally referred to as nodes, and the connection between the nodes (or the transportation modes) is referred to as the arcs. Despite several useful studies and insights into SC adaptation in the presence of disruption, a general shortcoming of existing work, as stated by Ivanov,[10] is that SC dynamics are not considered while solving disruption problems. Consequently, the disruption models are solved as static events without considering the duration of disruption and recovery policies. To illuminate this uncharted area, in this work, we develop a SC model that aids decision-making during a disruption by considering strategies to hedge against disruptions and solve the problem dynamically using a discrete-time approach and the rolling horizon framework. In particular, the developed model addresses disruptions at the tactical SC scale by focusing on the following issues:

- Including alternative sourcing options in the model to improve the supplier flexibility
- Improving logistics robustness by adding multimodal transportation modes
- Capacity utilization and outsourcing are included in the model to improve the facility flexibility options
- Making available the option to use the customers' locations as backup warehouses to ensure that demands are met
- Approaching the SC disruption problem in a dynamic fashion by using the rolling horizon

The remaining of this article is organized as follows. Section 2 discusses the existing approaches to tackle the SC disruptions and identify the knowledge gap, and section 3 provides the problem statement and the proposed model and solution framework. Case studies in section 4 demonstrate the performance of the proposed framework. Finally, section 5 presents the conclusion.

2. LITERATURE REVIEW

Several studies have proposed strategies to build SC resiliency to hedge against or manage disruption. The strategies to manage disruptions can be categorized into three main groups: mitigation strategies, recovery strategies, and passive acceptance.[19] Mitigation strategies, such as multiple sourcing, alternative transportation modes, and increasing safety stock, act in advance of the occurrence of disruption, irrespective of whether disruptions actually occur.[20] Recovery strategies generally take action after the occurrence of a disruption. Examples of actions taken include alternative sourcing, rerouting of transport systems, and production rescheduling for future time points.[21] This method generally gives a good idea of when the SC becomes stable. Passive acceptance accepts the risk of disruptions without any action. This may be appropriate when mitigation or recovery strategies outweigh their potential advantages.[19]

The summary of literature reviews based on the type of disruptions, modeling approach, and decisions is presented in Table 1, alongside remarks on performance measures. It is observed that most works in the literature can be categorized as mathematical models (deterministic approach or stochastic) and simulation models. Furthermore, only a few papers consider multiple source disruptions. Also, decisions from most models focus on coordinating the flow of supply and demand to minimize total cost and maximize the profit or service level. Thus, decisions are tactical and operational. However, some papers, particularly those with facility disruptions, also consider location/relocation decisions along with operational decisions. The review of the disruption approach framework is discussed under two main categories: simulation approaches and mathematical programming methods.

Simulation models have been used to study how different SC entities interact, and they have been proved to be an efficient and reliable tool for the analysis of SC design over a given time.[2,22] Some known simulation approaches used for the SC model including system dynamics (SD), discrete event simulation (DES), agent-based modeling, Monte-Carlo simulation, and Bayesian belief network have been used to describe the SC as a system. Wu et al.[23] applied a Petri net (PN) to a four-tier SC. The PN is a discrete event graphical and mathematical modeling tool. It modeled the propagation of

Table 1. Summary of Literature Reviews for Various Models

	modeling approach			
	MIP	stochastic/robust programming	simulations	remarks
supply disruption	Hasani and Khosrojerdi;[59] Lim et al.;[60] Bimpikis et al.[25,26]	Sawik;[56] Jahani et al.;[57] Sadeghi et al.;[62] Baghalian et al.[64]	Ivanov and Dolgui;[38] Wu et al.;[23] Wang et al.;[35] Guetter and Spinler;[37] Schmitt and Singh;[40,41] Singh et al.;[39] Otto et al.;[44] Behdani et al.;[45] Ledwoch et al.[46]	decisions made for the mathematical models are purely operational performance measures: service level, profit, cost minimization, and minimization of safety stock stochastic models considering risk measures while the other MIPs consider multiple objectives
facility disruption	Rezapour et al.;[61] Lim et al.;[60] Olfat et al.;[27] Maliki et al.[28]	Sawik;[52,54] Gholami-Zanjani et al.[49]	Paul et al.;[19] Schmitt and Singh;[40] Ivanov and Dolgui;[38] Wu et al.;[23] Kano et al.;[24] Wang et al.[35]	models make strategic and tactical decisions most simulation approaches offer recovery strategies performance measure includes fixed and variable costs and inventory policies
transportation disruption	Liu and Song;[29] Wagenaar et al.;[30] Paul et al.;[31] Sarkar et al.;[32] Albertzeth et al[33]	Özçelik et al.;[58] Azad et al.;[63] Xu et al.[34]	Wang et al.;[35] Schuh et al.;[36] Singh et al.;[39] Fartaj et al.[1]	few models consider logistic disruptions performance measures include service level, delivery time, profits, and total cost minimization.

disruptions, where the production process was modeled at an operative level, and considered the cost and lead time increase of a disruption. This network analyzed different policies and designs for lead time and cost effects by considering a three-echelon SC with safety stock. Kano et al.[24] used a PN to dynamically model the recovery of the SC after a disruption occurs. On the supply side, backup suppliers were used to hedge against disruption.

Using SD, Wang et al.[35] and Schuh et al.[36] built a multiechelon SC where the effect of different mitigation strategies when disruptions occur were evaluated. The performance measure was the inventory level, unmet demands, and total profits. Guetter and Spinler[37] built a SD model to capture the internal dynamics of operational risks of an enterprise under the influence of supply risks. The model was designed for disruptive shocks but also incorporates a degree of self-stabilization. DES models generally consider a system as a discrete sequence of events in time. Ivanov[2,38] used the DES to model a four-level SC to quantify the effect of two disruptive scenarios and the corresponding recovery process. Another DES model was used to predict the impacts of the pandemic on SC performance, defining performance based on the lead time, service level, and fulfillment rate. Singh et al.[39] developed a simulation model to analyze the responsiveness level of the food SC in India in the era of the Covid-19 pandemic. The outcome of both studies was the observation that SC operations and performance undergo drastic degradation under the pandemic conditions, thus suggesting the need for adaptation strategies. Schmitt and Singh[40] implemented a four-echelon SC into a DES model to test the impact of 20 days of disruption on the demand fulfillment rate and total SC inventory. A downstream disruption is shown to be more severe than an upstream disruption. Schmitt and Singh[40,41] studied DES to analyze the performance of a three-tier SC with two products (low-volume and high-volume), two raw material suppliers, three distribution centers, and predefined mitigation strategies. The agent-based approach has also been used to address SC dynamics. In the agent-based modeling approach, a multiagent system is used to represent stakeholders (social, economic, and ecological). Each stakeholder consists of agents, a set of relationships, and the agents' environments within the boundaries of an overarching system. Moreover, an agent is an autonomous, self-directed, individual entity that functions independently from other agents.[22,42,43] Using agent-based modeling, Otto et al.[44] assessed the propagation of losses in the global SC network because of natural disasters of different sizes, using the Japanese automotive manufacturing industry as a case study. Behdani et al.[45] applied an agent-based simulation framework for SC disruption management of a lube oil SC. This simulation framework provides a flexible modeling and simulation environment for decision-makers to experiment with different disruptions and management strategies. The application of the simulation model to support decision-making in different steps of the pre and postdisruption management processes is illustrated using a lube oil SC case study. Ledwoch et al.[46] used the agent-based method to quantitatively compare the consequence of different disruption frequencies and duration on the demand fulfillment, backlog, and inventory cost. In general, the simulation approaches are good approaches to studying the effect of disruptions and proposing mitigation approaches. Readers are directed to Bugert and Lasch[47] for a comprehensive review of simulation approaches.

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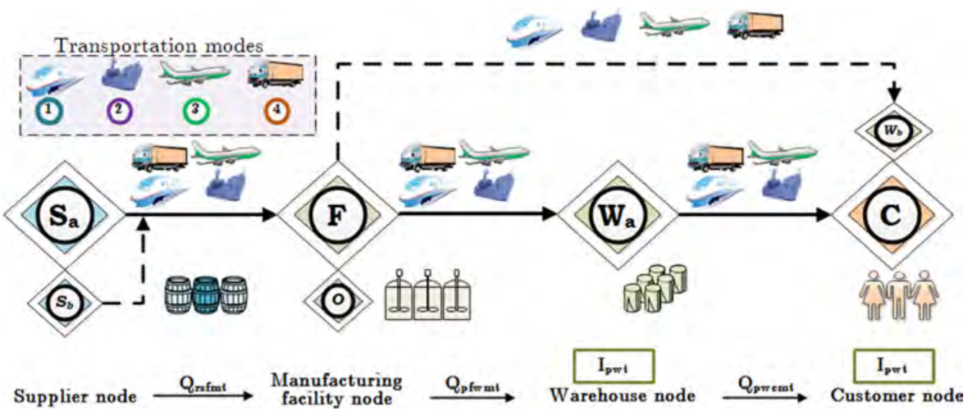

Figure 1. SC Topology.

Mathematical programming approaches have been used to study the effect of disruptions on SC designs and operations. At a high level, there are two approaches to incorporate disruptions into mathematical models when the entities (nodes or connecting arcs) are disrupted. One approach removes the entity from the network topology during the disrupted times, that is, the entities are not considered while solving the optimization problem, and the other approach treats the entity's capacity as a random variable leading to a stochastic formulation.[14,48] In both approaches, mathematical formulation leads to mixed-integer programming (MIP) models. The difference between the mathematical modeling approaches is in the redundancies used to hedge against disruption. Major studies in the area of the SC include the MIP models that incorporate a reliable backup supplier, which can be used if a primary supplier is disrupted, and the recovery costs are incorporated into objective functions.[11,14] Also, some studies have considered a joint inventory-location model under the risk of stochastic facility disruptions.[49−51] It is interesting to note the studies by Sawik,[52−54] who used a stochastic MIP approach to integrate supplier selection, demand allocation, and customer order scheduling in a multiechelon SC under disruption and further improved the model to jointly optimize supplier, production, and distributions.[55,56] Furthermore, Jahani et al.[57] used a two-stage MIP model to study the impact of capacity/inventory disruption on a supplier's cost when the supplier has different service agreements with customers. The model can assist suppliers in determining their capacity level and location, allocating capacity to customers, and negotiating service level terms. Özçelik et al.[58] analyzed the impact of the ripple effect on the performance of a reverse SC using robust optimization. They concluded that including reverse logistics in the ripple effect analysis is useful in a closed-loop SC for ripple effect mitigation. Hasani and Khosrojerdi[59] used an MIP model to investigate resilience in light of correlated disruptions. The solution is implemented as a Taguchi-based memetic algorithm that incorporates a customized hybrid parallel adaptive large neighborhood search. The memetic algorithm incorporates the Taguchi method to evaluate the search space. Lim et al.[60] considered a facility location problem in the presence of random disruption; they investigated the impact of misestimating the disruption probability and misestimating the correlation degree. Results indicate that the impact of disruption is much significant. Gholami-Zanjani et al.[49] applied stochastic programming/robust optimization to study the resilient SC design and inventory decisions, considering food product-specific characteristics and potential disruptions. Such a model allows the analysis of three resilience strategies to hedge against ripple effects caused by food disruptions. Rezapour et al.[61] proposed a SC network design problem under competition and disruption. The model is designed to find the most profitable network and risk mitigation policies. Sadeghi et al.[62] developed a multiobjective model for designing a SC network, considering resilience and sustainability and used a robust scenario-based stochastic programming approach for potential disruption scenarios. This approach allows the average performance of the SC in each objective to improve. Azad et al.[63] studied the design of a SC network in the presence of random disruption in the capacity of distribution centers and transportation modes. Conditional value at risk (CVaR) was used to control the risk of the decisions made in the presence of disruptions. Baghalian et al.[64] developed a stochastic mathematical formulation for designing a network of multiproduct SCs. The model simultaneously considers demand and supply uncertainties and investigates the impact of strategic facility location decisions on the SC's operational inventory and shipment decisions. The central theme of the mathematical programming approaches and simulations methods used in the literature has been used to address the disruptions in a proactive or reactive manner. In the proactive approach, disruptions are anticipated, and the decisions are made to mitigate the disruption before occurrence, while the reactive approach makes decisions when disruptions happen. It is interesting to note that both strategies have its pros and cons. Interested readers are directed to the review articles by Kamalahmadi and Parast,[65,66] Shekarian et al.,[9] and Ivanov et al.[10,67]

Many real-world optimization problems contain coupled decisions over a large timespan which typically cannot be solved in an integrated fashion. For such problems, the full optimization problem often contains an enormous number of variables and constraints and typically cannot be solved within a reasonable time. The rolling horizon has proved effective in such cases. This approach aims to exploit the underlying time structure of the problem such that only time points that have effects on the initial decisions are considered. The rolling horizon has been applied to a variety of problems, including energy storage problems,[68] scheduling,[69−71] and deterministic and stochastic SC problems,[5,72−77] and has proved to be effective in providing feasible solutions to large multiperiod problems.

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In the literature covered, most studies considered disruption in a single stage, and a limited number of studies covered multiple disruptions in the SC on a real-time basis. Most simulation studies offer recovery and passive strategies and are hence used to study the interactions of events and their possible outcomes, and mathematical models offer mitigation strategies. However, these mathematical models consider disruption as a static event; that is, the recovery time is not included in the model. Moreover, few studies consider transportation disruption. To cover some of the gaps found in the literature, the major contribution of this paper is to propose a framework that integrates multiple strategies into a multiechelon SC network so as to improve decision-making during disruption at the tactical and operational levels, that is, in considering the disruption, we have incorporated multiple buffers to ensure that the disruption effects are quelled. Also, we have approached the solution in a dynamic fashion to model more realistic situations by using the rolling horizon. In what follows, we describe the problem statement and how we have considered the modeling framework to address the SC under disruptions.

3. PROBLEM STATEMENT AND THEORETICAL FRAMEWORK

In this study, we consider a multiproduct, four-echelon customer-driven SC network with a set of nodes representing supplier ($s \in S$), manufacturing facilities ($f \in F$), warehouses ($w \in W$), and customer zones ($c \in C$), as shown in Figure 1. Arcs connect adjacent nodes. The SC network topology is such that there are strategies to ensure robust delivery for each entity in a disruption. The strategies employed include flexibility, redundancy, and collaboration between the nodes. The arcs represent the connecting links between nodes, and embedded in each arc are ($m \in M$) modes of transportation. It should be noted that each mode is different in reliability, which also affects the cost of the transportation modes. The horizon is discretized into T planning periods which is denoted by $t \in \{1, ..., |T|\}$. The supplier set S contains a set of main supplier $s \in S_a \subset S$ and backup suppliers $s \in S_b \subset S$. Such a strategy ensures that raw materials are delivered, irrespective of the disruption. It should be noted that the main suppliers are preferred for two major reasons, the cost of supply α_s is lower and the quality of the raw material supply θ_{rs} is better. The quality and the cost are directly incorporated into the model. Thus, the backups are only used when main suppliers are disrupted. At the manufacturing facility, there are $|F|$ facilities, and each facility operates at a unit production cost α_f^v. Also, each facility has potential for expansion where extra units $u \in U$ with capacity, C_u,are added to the main production unit. This comes at a cost of α_f^u. Furthermore, products that cannot be met even after facility expansion can also be outsourced. The warehouse $w \in W$ consists of a set of main warehouse $w \in W_a \subset W$ which are owned by the enterprise and backup warehouse $w \in W_b \subset W$ that are at the customer locations. The main warehouses also employ the flexibility strategy where the capacity is expandible at an extra cost. Following similar logic to that of the facility, using those units comes at an extra cost α_w^u. It should be noted that the inventory cost at every warehouse is given as α_w^{inv}. Furthermore, it is worth noting that inventory cost is higher at the customer's location than at the main warehouse. At every period t,each customer $c \in C$ has a demand, d_{pct}, for product $p \in P$. The product demand is either fully met by the supply from warehouses (main and backup), or the order is outsourced. The outsourced demand is transferred directly to the customer locations, and the cost of transportation is included in the overall outsourcing source. If the orders cannot be met, a penalty cost, α_c^{pen},is incurred. Products p and raw materials r are transported between nodes through the arcs, and each arc has a dimension m which is equal to the number of available transportation modes. Also, the variable unit cost associated with traversing from node i to j using mode m in arcs is given by α_{ij}^m where $i, j \in \{S, F, W, C\}$.

Expanding more on the demands, d_{pct},for a given customer order, the goal of the SC is to optimally select entities to satisfy the demands. The nature of the demands is such that at some periods,$t \in t_{certain}$, where $t_{certain}$ are the time periods with certain demands. It is assumed that the demand comes from a given distribution for the forecasted periods. Furthermore, for the forecasted period, demand scenarios (D_{pct}^s) are obtained by sampling the demand distributions, each scenario is assumed equiprobable, and the forecasted demands are obtained by taking the expectation over all scenarios. This is represented by eq 1.

$$d_{pct} := \left\{ \sum_s P^s D_{pct}^s \;\middle|\; \sum_s P_s = 1;\; t > 1 \right\} \forall\, p,\, c,\, t \neq t_{certain} \tag{1}$$

The network can encounter disruption at nodes and arcs, and each of the nodes responds to the disruption in different ways. There are subsets of main suppliers and backup suppliers on the supplier side. The backup suppliers are invoked once the main supplier is disrupted. Disruption is managed at the manufacturing facility by increasing the production capacity of undisrupted facilities and outsourcing a portion of the products to maintain a high service level. The unsatisfied demands are deemed to be lost sales. The warehouse follows the same strategy as the manufacturing facility by increasing storage capacity. Furthermore, inventory is consolidated with warehouses at customer locations for increased inventory cost. It should be noted that the problem considered here takes the design of the SC as fixed by a higher level (strategic level). This design also includes buffers to hedge against disruptions. The main purpose of the optimization is thus to adapt resource supply, production levels, and storage levels to demands for products, taking the capacity utilization, resource availability, and disruption forecasts into account. The results obtained will allow one to optimize inventory levels, improve coordination between nodes, and remove redundant buffers between SC entities. The main decisions are raw material quantities from suppliers, production levels at manufacturing sites, capacity utilizations at the warehouses and manufacturing sites, and transportation modes and quantities for each link in the SC network. The overall goal is to minimize the total cost and maintain a high service level. Thus, we want to utilize nodes at minimum cost in the network structure and find the flow path that transfers commodities at the lowest cost. The assumptions are explicitly stated below.

3.1. Model Formulation.

This section introduces the mathematical model for the SC under disruption. Applying the notations as shown in the appendix, the proposed MILP model for the SC under disruption is presented. First, we discuss the constraints and then formulate the objective function.

3.2. Constraints.

3.2.1. Supplier Disruption. At the supplier nodes, the main suppliers that are undisrupted, $S_{a,t}^n$, are selected before considering backup suppliers. Eq 2a ensures this selection. Once the selection of suppliers is done, eq 2b limits the capacity of these suppliers.

$$y_{s,t} - y_{s',t} \geq 0 \;\forall\; s \in S_{a,t}^{n};\; s' \in S_b,\; t \in T$$

$$y_{s,t} = \begin{Bmatrix} 1, \forall\; s \in S_{a,t}^{n} \\ 0, \forall\; s \in S_{a,t}^{d} \end{Bmatrix} \tag{2a}$$

$$\sum_{f}^{F}\sum_{m}^{M} Q_{rsfmt} \leq y_{st}\mathrm{Cap}_s \;\forall\; s \in S,\; r \in R,\; t \in T \tag{2b}$$

3.2.2. Facility Disruption. At the facility nodes, eq 3a restricts operations to only nondisrupted facilities, F^n, and ensures that facilities that are nondisrupted operate in full mode before expansion consideration. Eq 3a enforces feasible integer selection, while eq 3b enforces that the amount produced does not exceed the design capacities, and eq 3c sets restrictions on the quantity of products that can be outsourced.

$$y_{f,t}^{u} - y_{f,t}^{u'} \geq 0 \;\forall\; u < u'; f \in F;\; t \in T$$

$$y_{f,t}^{u=1} = \begin{Bmatrix} 1, \forall\; f \in F^{n};\; t \in T \\ 0, \forall\; f \in F^{d};\; t \in T,\; t < t_{\mathrm{R}} \end{Bmatrix} \tag{3a}$$

$$\sum_{p}^{P}\sum_{w}^{W}\sum_{m}^{M} Q_{pfwmt} \leq \sum_{u}^{u} y_{f,t}^{u} \times Cap_{f^{u}} \qquad \forall\; f \in F;\; t \in T$$

$$\sum_{p} Q_{pct}^{\mathrm{o}} \leq C^{\mathrm{o}} \;\forall\; c \in c,\; t \in T \tag{3c}$$

3.2.3. Warehouse Disruptions. For the warehouses, there are main warehouses, and retailer location sites are used as backup warehouses. Only the main warehouse can be disrupted and expanded. The capacity of the undisrupted warehouses W_a^n can be increased. Eq 4a ensure the selection and feasible expansion of undisrupted warehouses by fixing the selection of disrupted warehouses W_a^d to zero. Following that, eq 4b imply fixed capacity of the undisrupted warehouses is to be used before considering the backup warehouse W_b located at the retailer locations. Eqs 4c and 4d ensure that the inventory is within the utilized capacity range, while eq 4e enforces that materials stored at a customer location should service only that customer.

$$y_{w,t}^{u} - y_{w,t}^{u'} \geq 0 \qquad \forall\; u < u'; w \in W;\; t \in T$$

$$y_{w,t}^{u=1} - y_{w',t} \geq 0 \;\forall\; w \in W_a^{n};\; w' \in W_b;\; t \in \mathbb{T} \tag{4b}$$

$$\sum_{p}^{P} I_{pwt} \leq \sum_{u}^{u} y_{w,t}^{u} \times Cap_{w^{u}} \qquad \forall w \in W_a^{n};\; t \in T$$

$$\sum_{p}^{P} I_{pwt} \leq y_{w,t} \times \mathrm{Cap}_w \;\forall\; w \in W_b;\; t \in T \tag{4d}$$

$$\sum_{m}^{M} Q_{pwcmt} \coloneqq 0 \;\forall\; w = c;\; w \in W_b;\; t \in \mathbb{T} \tag{4e}$$

3.2.4. Transportation Capacity. The transportation links are multimodal, and each mode can be disrupted; whenever this happens, flow is redistributed between the available arc modes. Each of the transportation modes is limited by capacity, as shown in eqs 5a and 5c. For all the links.

$$\sum_{r}^{R} Q_{rsfmt} \leq y_{m,t}^{sf} \times \mathrm{tCap}_m^{sf} \;\forall\; s \in S;\; f \in F;\; m \in M;\; t \in T \tag{5a}$$

$$\sum_{p}^{P} Q_{pfwmt} \leq y_{m,t}^{fw} \times \mathrm{tCap}_m^{fw} \;\forall\; f \in F;\; w \in W;\; m \in M;\; t \in T \tag{5b}$$

$$\sum_{p}^{P} Q_{pwcmt} \leq y_{m,t}^{wc} \times \mathrm{tCap}_m^{wc} \;\forall\; w \in W;\; c \in C;\; m \in M;\; t \in T \tag{5c}$$

3.2.5. Flow Balances. The flow balance ensures continuity between the nodes through arcs. These balances are written for all nodes and are described by eqs 6a6b6c, respectively.

$$\sum_{w}^{W}\sum_{m}^{M} Q_{pfwmt} = \theta_{rp}{}^{*}\sum_{s}^{S}\sum_{m}^{M} Q_{rsfmt} \;\forall\; f \in F,\; r \in r,\; p \in P,\; t \in T \tag{6a}$$

$$I_{pwt} = I_{pwt-1} + \sum_{f}^{F}\sum_{m}^{M} Q_{pfwmt} - \sum_{c}^{C}\sum_{m}^{M} Q_{pwcmt} \;\forall\; p \in P,\; w \in W,\; t \in T \tag{6b}$$

$$d_{pct} - \sum_{w}^{W}\sum_{m}^{M} Q_{pwcmt} + Q_{pct} = B_{pct} \;\forall\; p \in P,\; c \in C,\; t \in T \tag{6c}$$

3.2.6. Objective Function. The objective function consists of the summation of all costs incurred and can be decomposed into three components, the cost of producing materials at the nodes, the cost of material flow across the arcs, and the penalties incurred for not meeting the retailer's demands. Quantitatively, this is captured in eq 7a

$$\begin{aligned} \mathrm{totalCost} = {} & \sum_{s}^{S}\sum_{t}^{T} (\mathrm{supCost}_{s,t} + \mathrm{sTCost}_{s,t}) \\ & + \sum_{w}^{W}\sum_{t}^{T} (\mathrm{whCost}_{w,t} + \mathrm{wTCost}_{w,t}) \\ & + \sum_{f}^{F}\sum_{t}^{T} (\mathrm{fTCost}_{f,t} + \mathrm{fTCost}_{f,t}) \\ & + \sum_{t}^{T} \mathrm{outCost}_t + \sum_{p}^{P}\sum_{c}^{C}\sum_{t}^{T} (B_{pct} \times \alpha_c^{\mathrm{pen}}) \end{aligned} \tag{7a}$$

The breakdown of the cost components is shown in eqs 7b7c7d7e7f

$$\mathrm{supCost}_{s,t} = \sum_{r}^{R}\sum_{f}^{F}\sum_{m}^{M} (Q_{rsfmt} \times \alpha_{rs}) \;\forall\; s \in S,\; t \in T \tag{7b}$$

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$$\mathrm{sTCost}_{s,t} = \sum_{r}^{R} \sum_{f}^{F} \sum_{m}^{M} Q_{rsfmt} \times \alpha_m^{sf} \ \forall\ s \in S;\ t \in T \tag{7c}$$

$$whCost_{w,t} = \left(\sum_{p}^{P} I_{pwt} \times \alpha_w^{inv}\right) + \left(\sum_{u>1} y_{w,t}^{u} \times \alpha_w^{u}\right) + \left(\alpha_{w|\,w\in W^d}^{rec}\right) \forall\ w \in W\,;\ t \in T$$

$$\mathrm{wTCost}_{w,t} = \sum_{p}^{P} \sum_{c}^{C} \sum_{m}^{M} Q_{pwcmt} \times \alpha_m^{wc} \ \forall\ w \in W;\ t \in T \tag{7e}$$

$$\mathrm{facCost}_{f,t} = \left(\sum_{w}^{W} \sum_{m}^{M} Q_{pfwmt} \times \alpha_f^{\mathrm{op}}\right) + \left(\sum_{u}^{\mathcal{U}} y_f^{u} \times \alpha_f^{u}\right) + (\alpha_{f|\,f\in F^d}^{\mathrm{rec}}) \tag{7f}$$

$$\mathrm{fTCost}_{f,t} = \sum_{p}^{P} \sum_{w}^{W} \sum_{m}^{M} Q_{pfwmt} \times \alpha_m^{fw} \ \forall\ f \in F;\ t \in T \tag{7g}$$

$$\mathrm{outCost}_{t} = \sum_{p}^{P} \sum_{c}^{C} Q_{pct} \times \alpha_{\mathrm{o}} \ \forall\ t \tag{7h}$$

After every optimization step, three metrics are used to quantify the efficiency of the solution, as shown in eqs 8a8b8c.

$$\mathrm{unitCost}_{t} = \frac{\left(\sum_p^P \sum_c^C \left(\sum_w^W \sum_m^M Q_{pwcmt} + Q_{pct}\right)\right)}{\mathrm{totalCost}_t} \tag{8a}$$

$$\mathrm{serviceLevel}_{t} = \frac{\left(\sum_p^P \sum_c^C \left(\sum_w^W \sum_m^M Q_{pwcmt} + Q_{pct}\right)\right)}{\sum_c \sum_p d_{pct}} \tag{8b}$$

$$\mathrm{SCEfficiency}_{t} = \frac{\left(\sum_p^P \sum_c^C \left(\sum_w^W \sum_m^M Q_{pwcmt}\right)\right)}{\sum_c \sum_p d_{pct}} \tag{8c}$$

Eq 8a represents the cost of supplying one unit of product to the customer, which determines the profit an enterprise makes if the selling price is fixed or determines the main price to deliver to customers if there is a limit on profit margin. Thus, a lower unit cost indicates that the SC achieves a service level at a low cost, and a higher unit cost indicates that the SC achieves a service level at a higher cost; the latter happens when most demands are outsourced; disruption also increases unit costs. Eq 8b quantifies the service level, which is the fraction of the demand that the SC meets. Finally, eq 8c shows the SC efficiency, which reflects the amount of products the SC meets without outsourcing.

3.3. Modeling Assumptions. Disruption is any event that affects the SC topology. To capture the nature of disruptions, we have made some modeling assumptions. The following assumptions are used in the proposed approach:

1. All SC entities can exist in two states: a normal state and a disrupted state. The entity is fully functional in the normal state, while the entities cannot function in the disrupted state.
2. Disruption can occur to both nodes (suppliers, facilities, and warehouses) and arcs (transportation routes between nodes), and in each disruption case, a subset of nodes and/or arcs are disrupted; once this happens, total capacity is lost. In the advent of disruption, the actions that can be taken are in these orders:
    a. Backup suppliers are only selected if there is no option to select the main suppliers. This is either due to disruptions or limited supplier capacity.
    b. Capacity expansion for manufacturing facilities and warehouses comes at a fixed cost.
    c. Outsourced demands are transferred to the customer directly.
    d. Once there is a disruption at the nodes or arcs, it takes time for the entity to recover.
3. Disruption of each node occurs independently; the interval is determined by the geometric distribution, which is the discrete counterpart of the exponential distribution.
4. In the event of disruptions, available measures provide alternatives, which come at extra costs to operations. Some of them are discussed below:
    a. When a manufacturing facility node is disrupted, product manufacturing can be outsourced, and recovery is amortized until the facility gets back to normal operation
    b. When transport arcs are disrupted, the transportation is redistributed, but the recovery fee is still present until the arc comes back to normal operation.
    c. When the warehouse nodes are disrupted, products are stored in the customer location for a specified cost.
    d. When supplier nodes are disrupted, alternate suppliers/backup suppliers are used to hedge against raw material demands.
5. A recovering facility cannot be disrupted until after full recovery. For this problem, it is assumed that the recovery time for disruption is two-unit time and comes at a cost. The cost is equally distributed within the periods. The incorporation of recovery time for SC entities using mathematical programming is nontrivial and, in principle, can be obtained via simulations by running the SC until stability is achieved.[10,12] The choice of two-unit time is considered here randomly to make sure that some recovery time is integrated into the model.
6. The model does not consider lead times between SC entities. The effect of lead time on a SC is important and should be considered at the operational level for higher accuracy. In this problem, we envisage that the inventory optimization approaches (storing products at customer locations and having safety stock to ensure no stock out) will reduce the effect of lead time. For more information, the reader is directed to the study by Brunaud et al.,[78] Cosma et al.,[79] and Spitter et al.[80]

To quantify the time the disruption happens, we have further assumed that the amount of time before the disruption happens is random, and the interval duration between disruptions follows a geometric distribution.[14] It should be noted that the choice of geometric distribution is because we have used a discrete-time model. The geometric distribution is

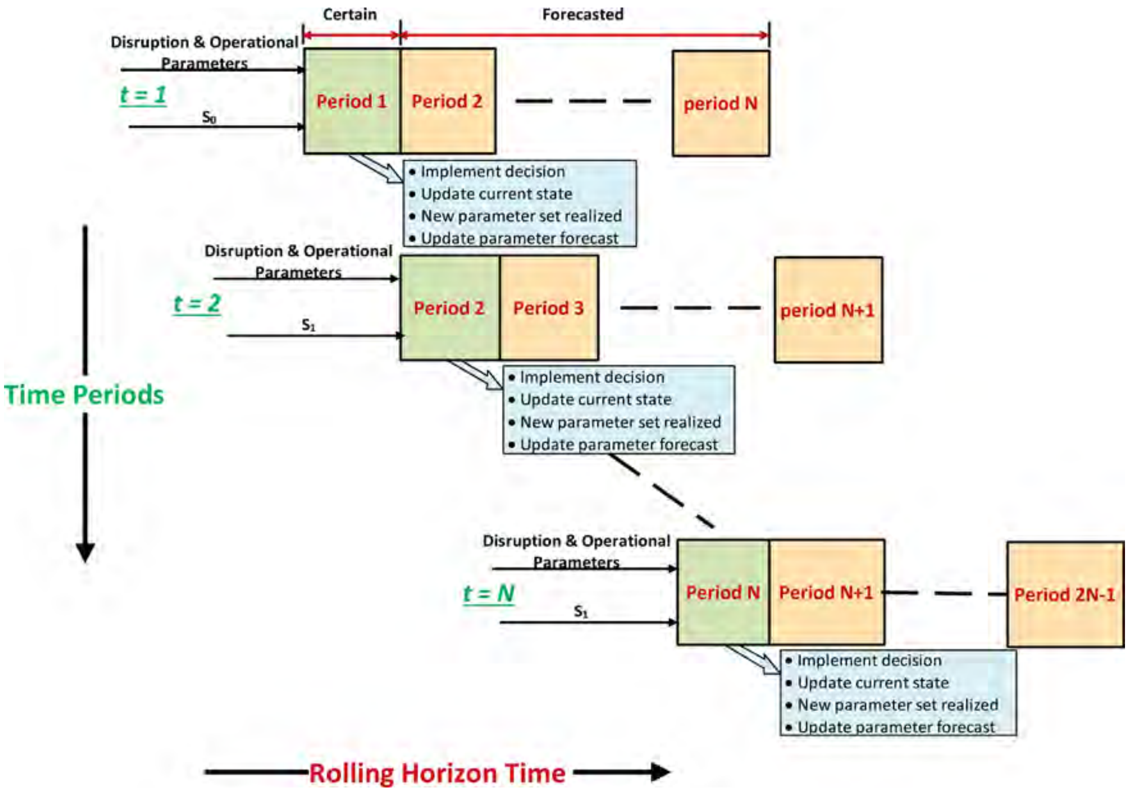

Figure 2. Illustration of the rolling horizon framework adapted to SC under disruption.

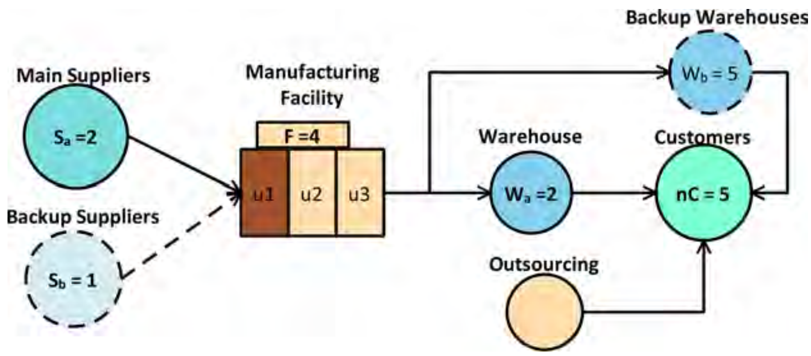

Figure 3. Supply chain network for case study1.

a discrete probability distribution that represents the probability of the number of successive failures before success is obtained in the Bernoulli trial.[81,82] The underlying assumption in using this distribution is that the average time between events is known, but the events' disruptions themselves are spaced at random. It is possible to have back-to-back disruptions, but we can also go weeks between disruptions due to randomness. Thus, we assume that the waiting time until the disruption is geometrically distributed with a parameter p (the average rate of occurrence), and the waiting times between each disruption are independent and geometrically distributed. The discretization of the time horizon considered is done according to the time interval for a possible disruption event. At each period, Bernoulli trial is performed, and if the trial leads to a success, then we have a disruption, otherwise there is no disruption. It should be noted that this procedure is done independently for all SC entities (nodes and arcs).

3.4. Rolling Horizon Framework. Owing to the uncertain nature of the demands at the future time periods, solving for optimal decisions for periods where the demands are uncertain will be suboptimal at the time of demand realization because of the differences between forecasted and realized demands. The SC model must be solved recursively when new demands are certain to mitigate performance degradation. This procedure can be realized within a rolling horizon approach. The idea, as explained in Figure 2, is as follows. For a given state of the SC model, prediction horizon (N) consists of period t with certain parameters and periods $t + 1$ to N where parameters are forecasted; the SC problem is solved over the entire prediction period N. As shown in Figure 3, for a given set of parameters P,the solution, returns the optimal decisions (θ_1^*, θ_2^*) . It should be noted that the set of parameters includes demands, the future state of entities, and operational costs. The optimal decisions for the certain period t are implemented, and the state of the SC network is updated based on the optimal decisions. The state of a SC is defined by the active nodes and

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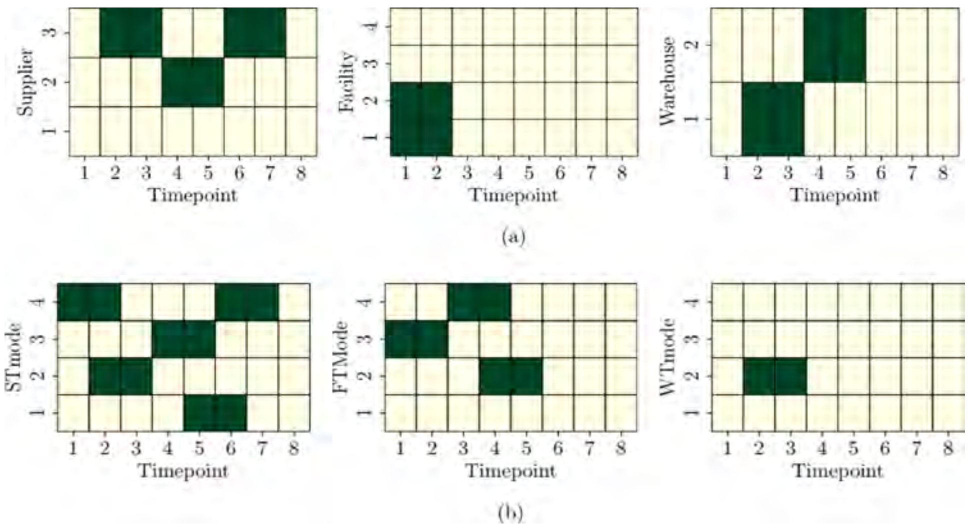

Figure 4. Disruption profile. (a) Node disruptions. (b) Arc disruptions. Dark squares indicate disruption times.

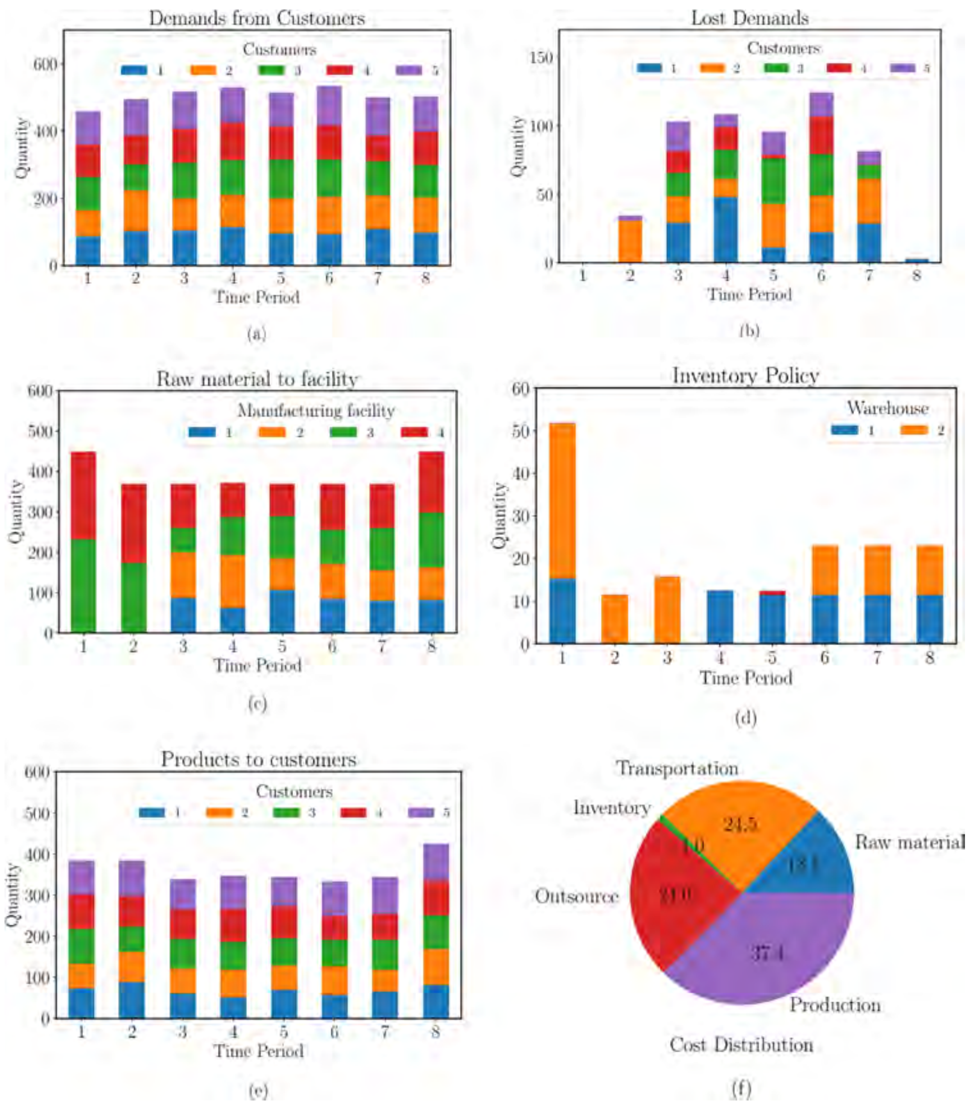

Figure 5. Breakdown of results obtained for response to disruption (a) Product demands from customers; (b) unmet demands; (c) raw materials to facility; (d) inventory amount; (e) products to customers; (f) cost distribution.

arcs, the inventory level in the undisrupted warehouses, and the current capacities of the operating facilities. Subsequently, the prediction horizon shifts by one time period ahead, and the procedure is repeated. This way, we are able to reduce the

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errors caused by the uncertain parameter by iteratively replacing the forecasts with the actual values over time.

4. RESULTS

In this section, we solve two case studies. In case study one, we analyzed the solution to a single disruption scenario problem, and we conducted a computational study on multiple scenarios for a given demand prediction. In this context, a single scenario means that a sample of possible disruptions across the horizon is considered. In case study two, a large SC problem is solved. The goal of the second case study is to fully implement the model for large-scale problems while considering the SC dynamics using the rolling horizon approach. In what follows, we describe the case studies in detail and show the solutions of each of them.

4.1. Case Study 1. In this problem, we study a single product setting, as shown in Figure 3, where a firm can source from two sets of suppliers: main suppliers, two suppliers, and a backup supplier. These suppliers differ in the quality of raw material, which determines the yield, and suppliers with better raw material quality are selected as the main supplier. The firm operates four manufacturing facilities, owns two warehouses, and supplies a single product to five retailers. In addition to the main warehouses, retailers' locations can be used as backup warehouses. This brings the total number of warehouses to seven. Within the SC network, there is the possibility of disruption of nodes (manufacturing sites, suppliers, and warehouses) and disruption in flow between the nodes. The flow between the nodes is managed using multimodal arcs, which can be translated into different transportation options between SC entities. It should be noted that the mode of transportation varies in capacity and reliability. The more reliable modes are more expensive.

The problem is to optimize the flow of raw materials, the flow of products, and the inventory of products to achieve a high customer service level (satisfy the retailer's demand) while maintaining profitability. These decisions must be made while considering disruption in the arcs and nodes. Moreover, the problem considers a bi-weekly time horizon, and new information is available every two days. Thus, the problem is solved by considering seven time periods, where only the first period is certain and the other six periods are forecasted. It should be noted that there are predicted disruptions during this forecasted period as well. Furthermore, the decisions made include the choice of suppliers, a quantity of materials across suppliers, choice of transportation modes from suppliers to facilities, choice of facilities and production quantity, transportation modes between facilities and choice of warehouses, choice of warehouse to supply retailers, and finally to outsource or not.

The model was formulated and solved in GAMS/CPLEX (v 38.2.1) on a PC with intel core i7-10510U, 2.30 GHz, and 16 GB of RAM. The model contains 6625 constraints, 3129 continuous, and 2740 binary variables. This study aims to answer two major questions: how does the SC network hedge against disruptions using the different strategies/options? What is the effect of arcs and node disruption on the SC? In what follows, the results show the answers to these questions.

4.1.1. Response to Disruptions. To answer this question, we set up a model to solve a single disruption scenario with demand for seven time periods, where only the first period is certain. The scenario disruptions are shown for the nodes in Figure 4a and arcs in Figure 4b, where the unavailable entities are displayed in green squares. It should be noted that the recovery time for all entities is equal to two time periods. Furthermore, Figure 4b shows the disruption connection links between supplier 1 and facility 1, facility 1 and warehouse 1, and warehouse 1 and customer 1. The y-axis indicates the transportation modes between each node. The model was solved to optimality, and the solver reports 492,453 iterations and 31,172 nodes with a computational time of 66 s.

The results obtained are shown in Figure 5, where Figure 5a, b shows the distribution of demands from all customers and the unmet demands at the customer nodes for all the periods considered in the problem. The nature of the demand follows what was described in section 3, and only the first period with the deterministic demand is implemented. Figure 5c−e shows how the SC entities are utilized, and the inventory policies adopted for the implemented period, respectively. Finally, the implemented cost profile is shown in Figure 5f where the pie chart shows the distribution of all costs.

According to Figure 5a, b, the model's response to demands, we observe that the demand for the implemented period was met, and the response to the demands for the forecasted period indicates that for the worst-case situation, 75% of the demand was met, and this is corroborated by Figure 5e the delivery to customer. Figure 5c, d shows the manufacturing site and warehouse utilization. Figure 5c shows the decision at the manufacturing facilities. In the first two periods, only the undisrupted facilities are used for production, and it should be noted that the capacity at this point is above the nominal capacity. At further periods where there is no disruption, production is decentralized, that is, all facilities are used for production and at the nominal capacity utilization. The decision at the manufacturing facility shows the tradeoff between the number of facilities in use and the available transportation modes. The manufacturing facility capacity utilization favors a decentralized approach. Such decentralization ensures that the cheapest transportation modes are used from each facility.

As seen in Figure 5d, the inventory amount for the first period was higher than every other period, higher inventory facilitates a reduction in production cost, but the choice increases inventory cost. This is due to the envisaged disruption for the first two facilities. The resultant of this is a reduction in production cost and utilization of the undisrupted facilities. According to the cost profile in Figure 5f, the largest percentage of the cost is due to production, followed by the cost of outsourcing part of the demand. A closer look at Figure 5c, d shows that in the selection of the SC entities, the model selects only available facilities and tradeoffs between the expansion of available facilities and outsourcing. Similarly, the model first selects the arcs with lower costs.

Based on the solution obtained, the strategy for achieving minimum cost is to maximize the utilization of the nodes with the lowest cost first before exploring the ones with higher cost. Furthermore, the utilization of the nodes is also linked to the availability of transportation networks with lower cost operating costs. It is worth mentioning that the multimodal transportation options and the capacity are also important because once the nodes are selected, the optimization problem selects the flow path that minimizes the total cost of the SC.

4.1.2. Effect of Arcs and Nodes. To study the effect of nodes and arcs disruptions, we set up a computational study for three cases of the MILP model. These three cases are (i) cases where all disruptions happen, (ii) cases where only nodes

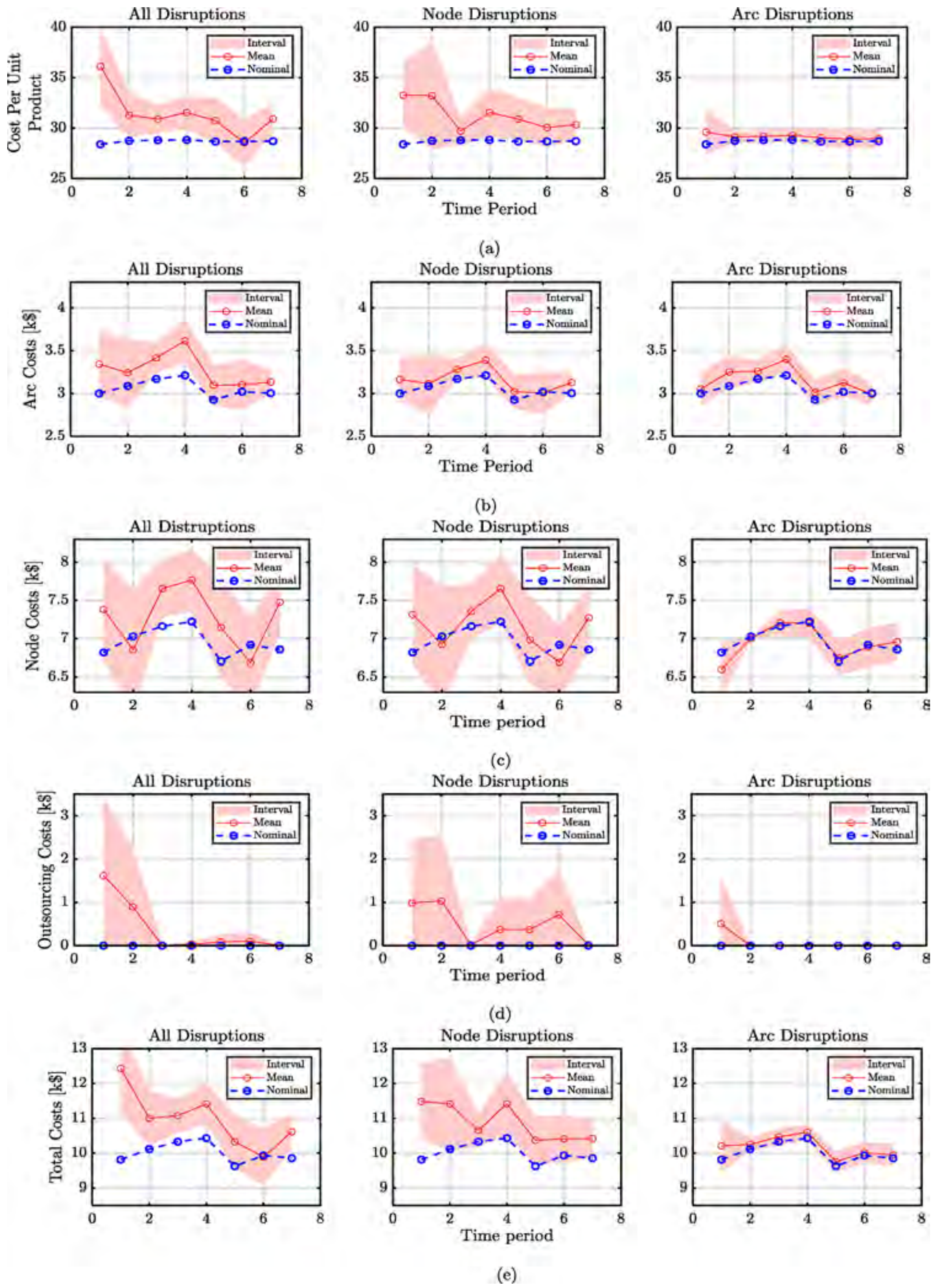

Figure 6. Computational results on effect of arcs and nodes: (a) Cost per unit products; (b) cost of operating arcs; (c) cost of operating nodes; (d) outsourcing costs; (e) total SC cost. Solid blue line: normal operations, shaded regions: confidence interval, and solid red line: mean value.

are disrupted, and (iii) cases where nodes and arcs are disrupted. By node disruption, we mean the disruption is considered for only suppliers, facilities, and warehouses, while arc disruption implies that only the flow network modes are disrupted.

Twenty disruption scenarios are solved for each case, and the solutions are reported with confidence bounds. The demand is kept constant for all disruption scenarios, and only the disruption situation changes; each case is solved with the same set of scenarios. Furthermore, the rolling horizon is used to solve all eight periods for a given scenario. Thus, each scenario consists of eight optimization problems. The average computational time for each scenario is 67, 104.52, and 154.56 s for cases 1, 2, and 3, respectively.

Figure 6 shows the solutions in terms of the different cost components. Solutions to each case are presented for every cost with the confidence interval associated with the 20 scenarios. Each subfigure compares different components for the three cases: all disruptions, node disruption, and arc disruption. Figure 6a compares the cost per unit product (or eq 8a) for all cases. Figure 6b compares the cost of operating arcs, which is the total transportation cost, for all cases. Figure 6c shows the comparison of the total cost of operating nodes which captures the cost of raw materials and the cost of operating the facilities, Figure 6d indicates the outsourcing cost for all cases, and Figure 6e compares the total incurred cost for operating all SC entities. Figure 7 shows the average inventory

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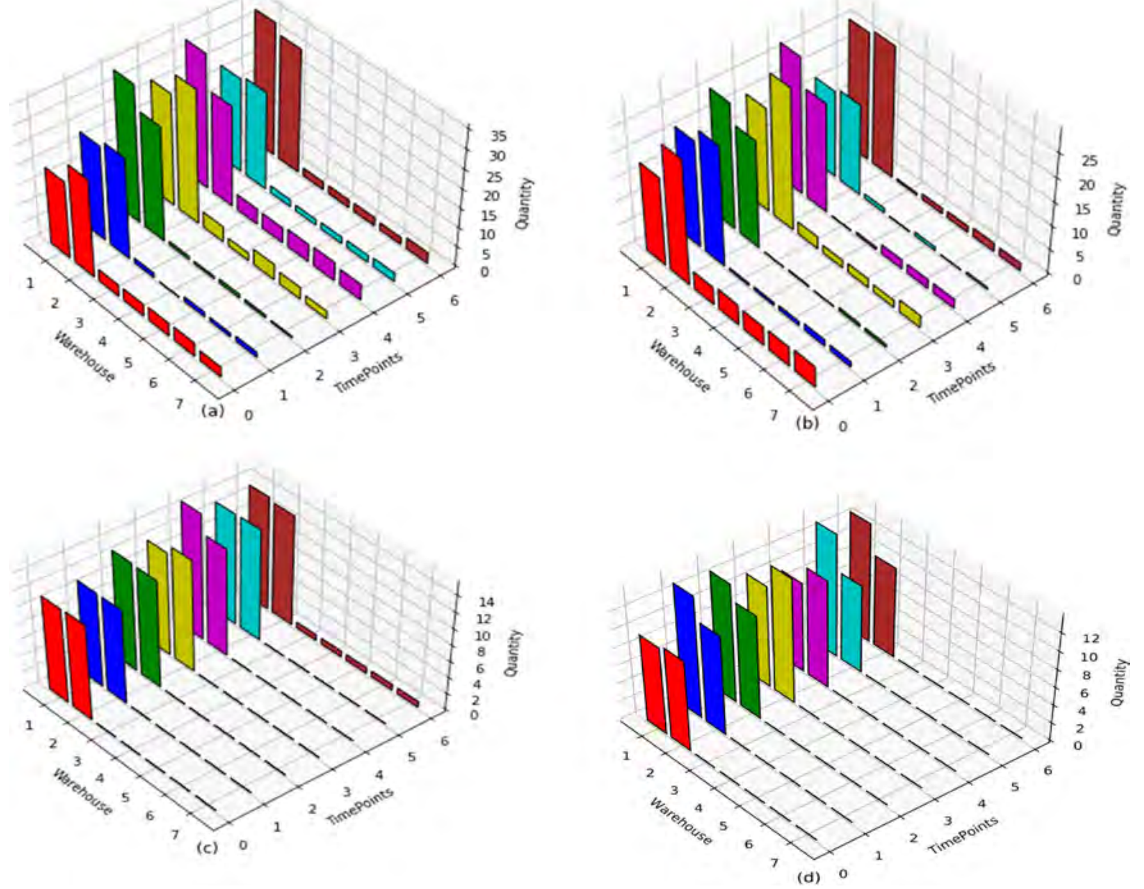

Figure 7. Inventory Policies: (a) Nodes and arc disruption; (b) node disruptions; (c) arc disruptions; (d) nominal operation.

decisions made for each of the cases. It should be noted that all results shown are solutions for the implemented time period.

It is important to note that for all conditions, the problem was set such that the SC meets all customer demand (i.e., 100% service level). This was done by setting the upper bound of the outsourced capacity (eq 3c) to a high value. Comparing the cost per unit products in Figure 6a, it is observed that the unit cost is greater for the case when all disruptions are considered, where it is the lowest when only arcs are disrupted. It should be noted that this cost is a major profit indicator if the service level is to be satisfied, and Figure 6a shows that the arcs are less likely to increase the cost per unit product. This is because the multimodal options offer a higher degree of flexibility to mitigate disruption. The SC problem can mitigate the effect at a minimal cost because there are many options. If one mode is not available for an arc, there are options to use other modes within the arc or explore other arcs where cheaper modes are undisrupted. Another general observation is the variability in response for all scenarios. Figure 6a−e shows that the variability, as shown by the confidence intervals, is less for disruptions in arcs. This implies that when arcs are disrupted, the SC can adjust itself such that the cost incurred is not much. Furthermore, observing the trends in total cost, the cost of operating nodes is greater than the cost of operating arcs. For each of the figures, the results are compared with the nominal case where there is no disruption. It can be observed that the cost per unit product and the arc costs are lower for the nominal cases when compared with the scenarios. However, when comparing the node costs, there is a variation in trend. There are some points where the node cost for the nominal cost is higher than that of the expected value, and this is because disrupted manufacturing nodes are not in operation, and most operations are outsourced. Thus, comparing Figure 6c and Figure 6d, it is observed that at time point where the nominal node cost is greater than the expected value of scenarios, the corresponding expected value of outsourcing cost is high. Finally, the nominal case shows a lower total cost at all time periods when compared with the disrupted scenarios. It should be noted that in this case study, the operating cost parameters for the nodes are greater than that of the arcs. We envisage that this is the most common situation, even when specialty freights are used. The scenario analysis shown for the arc disruption indicates that the cost of operating the arc does not deviate so much from that of the nominal operation. This is because of the robustness of the multimodal arcs. Moreover, the inventory policies, shown in Figure 7, are higher for cases where all entities are disrupted and lowest for the nominal cases. For node disruption, the undisrupted warehouse nodes are expanded at an extra cost. In this case, more products can be manufactured, and the excess is stored as inventory. A close comparison between the inventory decisions for the arc disruption, Figure 7c, and the nominal case, Figure 7d, indicates that the inventory approach is similar except at the last time point, that is, the backup warehouses are not used. The actual warehouses can take care of the disruptions at the arcs except at the last time point. It should be noted that this inventory increases the current incurred cost, holding down operating cash, and reduces the cost of manufacturing in the next period. Also, when entities are disrupted and inaccessible, the holding inventory compensates for the shortages, thus reducing the backorders.

4.2. Case Study 2: Multiproduct Network. The problem we address in this case study is a multiechelon, multiproduct SC network with *6 suppliers, 10 production facilities, 20 distribution centers,* and *15 customer locations*. At the supplier node, there are three main suppliers and three backup suppliers. Each facility can manufacture 20 different products at the facility level, with specific maximum capacity limits. However, there is a possibility for expansion if demand is high with an additional cost. Among the *20 warehouses,* there are *five* main *warehouses,* and the remaining *15* are at the customer location. These backup warehouses service the particular customer at a higher inventory cost. The problem is solved considering a time horizon of 2.5 months and one-week discretization. This leads to 10 discretization points, assuming 4 weeks make a month. Moreover, in the rolling horizon implementation framework, only the first period is deterministic; hence, the solution is implemented for that period while the inventory level is carried over to the next time point.

The proposed MILP model for case study 2 was formulated and solved using GAMS/CPLEX (v 38.2.1) on a PC with intel core i7-10510U/2.30 GHz and 16 GB of RAM. The relative optimality gap tolerance was set to 0.02. The model solved consists of 127,855 equations and 229,087 variables, where 16,156 are discrete variables, and the computational time required to solve the problem was 4371.86 s. Because the problem was solved using the rolling horizon framework, and there are 10 planning periods, thus, on average, each problem takes 440 s.

Figure 8a is a plot of the cost breakdown at each time period. The y-axis shows the cost incurred in thousands of dollars. Figure 8b shows the plot of service level and SC efficiency and the cost per unit product against the time. Figure 9a,b shows the inventory policies adopted in the main warehouses and backup warehouses, respectively. According to Figure 8a, the total cost is dominated by the node costs for most of the periods; also, as can be seen in the third time period, it has the highest total cost and the lowest node cost. This is because of the degree of disruption at the time point. As shown in Figure 8b, at the third time point, the SC network satisfies 70% of the total demand, and outsourcing can only satisfy a maximum of 10% of the total demand. The bulk of the cost is due to the penalty for unmet demands. The penalty cost for the unmet demands caused the increase. For other time periods where the service level is 100%, we noticed that the lowest unit cost is achieved when the internal and external service levels are equal. This suggests that outsourcing more products increases unit cost; therefore, to reduce the cost per unit of product, more redundancies can be added to ensure that the difference between SC efficiency and the service level is minimized. This points to improving the flexibility of the entire SC network. This includes accruing more inventory buffers and adopting modules that can be transported to sites where disruptions occur. Thus, a SC network should be designed for efficiency, which means to meet demand and obtain supply, as well as resiliency to adapt to changes in the event of disruption and maintain efficiency.

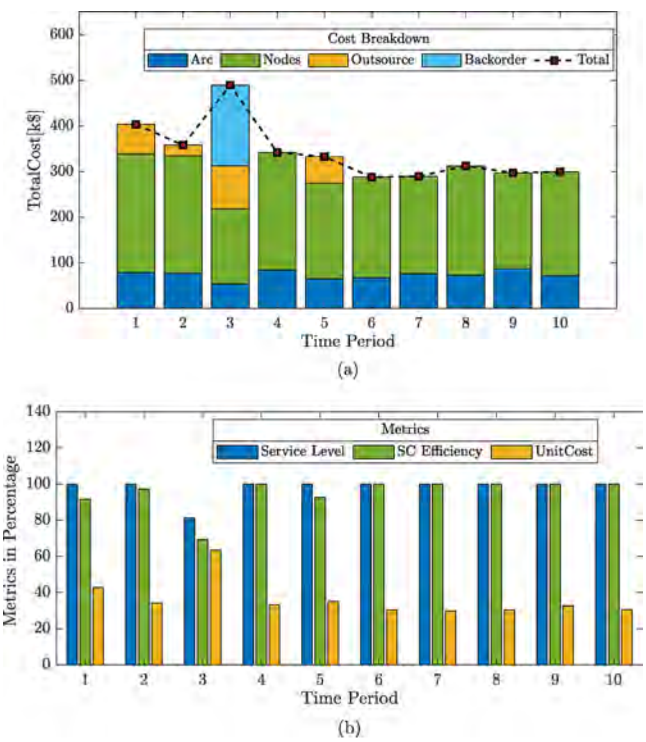

Figure 8. Analysis of cost for a large case study: (a) Cost breakdown. (b) Plot of service level and unit cost against time period.

4.3. Discussions of Results. The two case studies presented above confirm the efficacy of the model, its applicability to large problems, and its ability to provide insights regarding the state of the SC. In the first case study, we observed that the solution selects only available facilities and the tradeoff between expanding facilities and outsourcing products. Similarly, the selection is made for the available arcs with lower costs at the arcs. More importantly, probing deeper into the solution space shows that the decisions hinge on some of the equations. These are the available nodes, capacity limitations of the suppliers, and inventory flow balance. To curb the effect of suppliers on production in general, it is essential to operate an optimal raw material inventory as well. Although this comes at an additional cost, it will ensure that buffer materials are available in the event of supplier-side disruptions.

The second part of the first case study clearly shows that the SC's cost is dominated by the nodes in the absence of backorder. Also, there is higher cost variability at the nodes. It is important to reduce the cost variability at the nodes. To reduce the cost variability at the nodes, it is important to increase the degree of flexibility. One way to do this is to consider using mobile modular units by adapting the framework into studies by Allen et al.[83] or Allman and Zhang.[84] Modules that can be transported through the robust arcs can take advantage of the robustness of arcs to improve robustness at the manufacturing sites and warehouse nodes. Modules can be transported to node locations whenever a node is disrupted or expand the node's capacity when the demand is high. The arcs are less affected by the disruption, as indicated by the cost variability of all its components. This is because the available multimodal options will distribute the flow, avoiding disrupted arcs while maintaining minimal cost. It is not enough to achieve minimum cost because the transportation modes have reliability in terms of speed of delivery. The transportation modes can be exploited so that there is a tradeoff between the cost of the flow path and the reliability of delivery. Finally, the second case studies show

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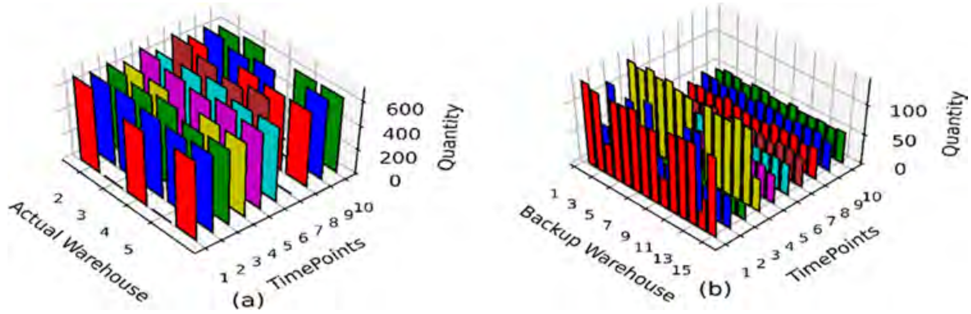

Figure 9. Inventory level for (a) actual warehouse and (b) backup warehouses.

how the model can be applied to a big realistic problem, and the solution emphasizes the need to strengthen the nodes or increase their flexibility. This would optimize cost and keep the network efficiency high. Representing the SC problem as a flow network, which consists of nodes connected by arcs, will help to design better strategies for resiliency and develop metrics that will measure how much a network can maintain and adapt its operational performance when facing disruptions.

5. CONCLUSIONS

This article discusses a novel approach to SC operations under disruptions. A mixed-integer linear program was developed to mitigate the effect of disruptions by adding redundancies to provide a buffer against various sorts of disruptions, including the cost of recovery, and considering the dynamics of a disruption using the rolling horizon approach. The various options considered are multisourcing, backup sourcing, expansion at the manufacturing facilities and warehouses, outsourcing, multimodal transportation options, and customer locations as backup warehouses. Moreover, the disruptions are random variables, and the outcome is determined before the optimization problem is solved. The developed model was applied to two case studies to measure the effects on the SC. Results suggest that the nodes dominate the total cost of the SC. Also, for similar product demands, the variability in cost obtained at the nodes is higher than that of the arcs. This is because of the multimodal options available for the arcs. A way to reduce the cost variability at the nodes is to improve flexibility by selecting transportable modules. This, however, will make the optimization problem more complex.

In consideration of SC design or SC expansion, it is important to design the SC for efficiency and resiliency. The proposed approach considers both and can thus be used for SC design problems. For this study, once a SC entity (link or node) fails, it is removed from the network topology before the optimization problem is solved, and the cost of bringing the entities back to a normal state is considered. Future direction would consider a stochastic approach where the capacities of the entity (nodes or arcs) will be treated as random variables.

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Notes

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NOTATIONS

Sets and Indices

S_a	sets of main suppliers; indexed by $s \in S_b$
S_b	sets of backup suppliers; indexed by $s \in S_b$
S	sets of all suppliers; indexed by $s \in S = S_a \cup S_b$
F	sets of manufacturing facilities; indexed by $f \in F$
W_a	sets of main warehouses; indexed by $w \in W_a$
W_b	sets of backup warehouses; indexed by $w \in W_b$
W	sets of all warehouses; indexed by $w \in W \supset W_a \cup W_b$
C	sets of customers; indexed by $c \in C$
P	sets of products ; indexed by $p \in P$
u	sets of units for capacity expansion; indexed by $u \in U$
T	sets of discretized timepoint; indexed by t
$S^n_{a,t}$, $S^d_{a,t}$	set of main suppliers S_a that are either disrupted,d or nondisrupted n at period t
F^n_t , F^d	set of facilities that are either disrupted,d or nondisrupted n at period t
W^n_a, W^d_a	set of main warehouses that are either disrupted,d or nondisrupted n at period t

Parameters

d_{pct}	the demand of customers c for product p at a period t
α_s	cost of supplying material r from customer s
α^u_w	fixed cost for unit u in warehouse w
α^{inv}_w	inventory holding cost in warehouse w
α^{pen}_c	penalty cost for unmet demand of customer c
α^{op}_f	operating cost for facility f
α^u_f	fixed cost for unit u in facility f
α^{rec}_w	recovery cost for warehouse w
α^{rec}_f	recovery cost for facility f
α_o	cost of outsourcing
$\alpha^{i,j}_m$	transportation costs for moving unit product from node $i \in \{s, f, w\}$ to $j \in \{f, w, c\}$ using transportation mode m

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$\mathrm{tCap}_m^{i,j}$ transportation capacity of mode m for moving unit products or raw materials from node $i \in \{s, f, w\}$ to $j \in \{f, w, c\}$

Cap_i the capacity of node $i \in \{s, f, w\}$

θ_{rp} the conversion factor for raw material r to products p

Decision Variables (Non-negative Continuous Variables)

I_{pwt} inventory of product p in warehouse w at period t

Q_{pwcmt} amount of product p transported from warehouse w to customer c using mode m at time t

Q_{pfwmt} amount of product p transported from facility f to warehouse w using mode m at time t

Q_{rsfmt} amount of raw material r from supplier to facility f by mode m at period t

Q_{pct} quantity of product p outsourced and transported to customer c at time t

B_{pct} amount of product p from customer c that is unmet at period t

Binary Variables

$y_{s,t}$ determines if supplier s is chosen at period t

$y_{f,t}^{u}$ determines if unit u is chosen at facility f and period t

$y_{w,t}^{u}$ determines if unit u is chosen at warehouse w and period t

$y_{m,t}^{sf}$ determines if mode m is selected between supplier s and facility f at period t

$y_{m,t}^{fw}$ determines if mode m is selected between facility f and warehouse w at period t

$y_{m,t}^{wc}$ determines if mode m is selected between warehouse w and customer c at period t

REFERENCES

(1) Fartaj, S.-R.; Kabir, G.; Eghujovbo, V.; Ali, S. M.; Paul, S. K. Modeling Transportation Disruptions in the Supply Chain of Automotive Parts Manufacturing Company. *Int. J. Prod. Econ.* **2020**, *222*, 107511.

(2) Ivanov, D. Predicting the Impacts of Epidemic Outbreaks on Global Supply Chains: A Simulation-Based Analysis on the Coronavirus Outbreak (COVID-19/SARS-CoV-2) Case. *Transport. Res. E: Log. Transport. Rev.* **2020**, *136*, No. 101922.

(3) *Toward a more resilient consumer supply chain|McKinsey*. https://www.mckinsey.com/business-functions/operations/our-insights/can-your-supply-chain-deliver-what-your-consumer-wants?cid=other-eml-dre-mip-mck&hlkid=21e61eeb91b64b5ea6ba1af582530332&hctky=10139374&hdpid=d8e576ed-13b7-483c-8ac6-2f7293cdf232# (accessed 2021-04-26).

(4) Chopra, S.*Supply Chain Management: Strategy, Planning and Operation*, 7th edition; Pearson Education: New York, NY, 2019.

(5) Bhosekar, A.; Badejo, O.; Ierapetritou, M. Modular Supply Chain Optimization Considering Demand Uncertainty to Manage Risk. *AIChE J.* **2021**, *67*, No. e17367.

(6) Badejo, O.; Ierapetritou, M. Integrating Tactical Planning, Operational Planning and Scheduling Using Data-Driven Feasibility Analysis. *Comput. Chem. Eng.* **2022**, *161*, No. 107759.

(7) Apap, R. M.; Grossmann, I. E. Models and Computational Strategies for Multistage Stochastic Programming under Endogenous and Exogenous Uncertainties. *Comput. Chem. Eng.* **2017**, *103*, 233−274.

(8) Wang, L.; Lu, Z.; Ren, Y. A Rolling Horizon Approach for Production Planning and Condition-Based Maintenance under Uncertain Demand. *Proc. IMechE* **2019**, *233*, 1014−1028.

(9) Shekarian, M.; Reza Nooraie, S. V.; Parast, M. M. An Examination of the Impact of Flexibility and Agility on Mitigating Supply Chain Disruptions. *Int. J. Prod. Econ.* **2020**, *220*, 107438.

(10) Ivanov, D.; Dolgui, A.; Sokolov, B.; Ivanova, M. Literature Review on Disruption Recovery in the Supply Chain. *Int. J. Prod. Res.* **2017**, *55*, 6158−6174.

(11) Snyder, L. V.; Scaparra, M. P.; Daskin, M. S.; Church, R. L.Planning for Disruptions in Supply Chain Networks. In *Models, Methods, and Applications for Innovative Decision Making*; Johnson, M. P., Norman, B., Secomandi, N., Gray, P., Greenberg, H. J., Eds.; INFORMS, 2006; pp. 234−257.

(12) Shekarian, M.; Mellat Parast, M. An Integrative Approach to Supply Chain Disruption Risk and Resilience Management: A Literature Review. *Int. J. Log. Res. Appl.* **2021**, *24*, 427−455.

(13) Chen, J.; Wang, H.; Zhong, R. Y. A Supply Chain Disruption Recovery Strategy Considering Product Change under COVID-19. *J. Manuf. Syst.* **2021**, *60*, 920−927.

(14) Snyder, L. V.; Atan, Z.; Peng, P.; Rong, Y.; Schmitt, A. J.; Sinsoysal, B. OR/MS Models for Supply Chain Disruptions: A Review. *IIE Trans.* **2016**, *48*, 89−109.

(15) *Resilient Supply Chain|Accenture*. https://www.accenture.com/us-en/services/supply-chain-operations/resilient-supply-chain (accessed 2022-04-14).

(16) Esmaeilikia, M.; Fahimnia, B.; Sarkis, J.; Govindan, K.; Kumar, A.; Mo, J. Tactical Supply Chain Planning Models with Inherent Flexibility: Definition and Review. *Ann. Oper. Res.* **2016**, *244*, 407−427.

(17) Mackay, J.; Munoz, A.; Pepper, M. Conceptualising Redundancy and Flexibility towards Supply Chain Robustness and Resilience. *J. Risk Res.* **2020**, *23*, 1541−1561.

(18) Ivanov, D.; Pavlov, A.; Pavlov, D.; Sokolov, B. Minimization of Disruption-Related Return Flows in the Supply Chain. *Int. J. Prod. Econ.* **2017**, *183*, 503−513.

(19) Paul, S. K.; Sarker, R.; Essam, D. Managing Risk and Disruption in Production-Inventory and Supply Chain Systems: A Review. *J. Ind. Manag. Optim.* **2016**, *12*, 1009−1029.

(20) Tomlin, B. On the Value of Mitigation and Contingency Strategies for Managing Supply Chain Disruption Risks. *Manag. Sci.* **2006**, *52*, 639−657.

(21) Lodree, E. J., Jr.; Taskin, S. An Insurance Risk Management Framework for Disaster Relief and Supply Chain Disruption Inventory Planning. *J. Oper. Res. Soc.* **2008**, *59*, 674−684.

(22) Sahay, N.; Ierapetritou, M. Supply Chain Management Using an Optimization Driven Simulation Approach. *AIChE J.* **2013**, *59*, 4612−4626.

(23) Wu, T.; Blackhurst, J.; O'grady, P. Methodology for Supply Chain Disruption Analysis. *Int. J. Prod. Res.* **2007**, *45*, 1665−1682.

(24) Kano, C.; Blos, M.; Junqueira, F.; Santos Filho, D.; Miyagi, P.Modeling And Analysis Of Global Supply Chain Disruption Based On Petri Net. In *ABCM Symposium Series in Mechatronics*; 2014; Vol. *6*, pp. 24−32.

(25) Bimpikis, K.; Fearing, D.; Tahbaz-Salehi, A. Multisourcing and Miscoordination in Supply Chain Networks. *Oper. Res.* **2018**, *66*, 1023−1039.

(26) Bimpikis, K.; Candogan, O.; Ehsani, S. Supply Disruptions and Optimal Network Structures. *Manage. Sci.* **2019**, *65*, 5504−5517.

(27) Olfat, L.; Amiri, M.; Teimoury, E.; Gevari, F. G. Real-Time Multiple Disruptions Management In a Multi-Level Supply Chain: A Recovery Planning Approach. *J. Manag. Stud.* **2018**, *16*, 79−104.

(28) Maliki, F.; Souier, M.; Dahane, M.; Ben Abdelaziz, F. A Multi-Objective Optimization Model for a Multi-Period Mobile Facility Location Problem with Environmental and Disruption Consideration. *Ann. Oper. Res.* **2022**, 1−26.

(29) Liu, X.; Song, X. Emergency Operations Scheduling for a Blood Supply Network in Disaster Reliefs. *IFAC-PapersOnLine* **2019**, *52*, 778.

(30) Wagenaar, J.; Fragkos, I.; Zuidwijk, R. Integrated Planning for Multimodal Networks with Disruptions and Customer Service Requirements. *Transport. Sci.* **2021**, *55*, 196−221.

(31) Paul, S. K.; Asian, S.; Goh, M.; Torabi, S. A. Managing Sudden Transportation Disruptions in Supply Chains under Delivery Delay and Quantity Loss. *Ann. Oper. Res.* **2019**, *273*, 783−814.

(32) Sarkar, B.; Mridha, B.; Pareek, S.; Sarkar, M.; Thangavelu, L. A Flexible Biofuel and Bioenergy Production System with Transportation Disruption under a Sustainable Supply Chain Network. *J. Cleaner Prod.* **2021**, *317*, No. 128079.

https://doi.org/10.1021/acs.iecr.2c01641
Ind. Eng. Chem. Res. 2022, 61, 16747−16763

(33) Albertzeth, G.; Pujawan, I. N.; Hilletofth, P.; Tjahjono, B. Mitigating Transportation Disruptions in a Supply Chain: A Cost-Effective Strategy. *Int. J. Log. Res. Appl.* **2020**, *23*, 139−158.
(34) Xu, L.; Ng, T. S. A. A Robust Mixed-Integer Linear Programming Model for Mitigating Rail Transit Disruptions Under Uncertainty. *Transport. Sci.* **2020**, *54*, 1388−1407.
(35) Wang, Z.; Hu, H.; Gong, J. Simulation Based Multiple Disturbances Evaluation in the Precast Supply Chain for Improved Disturbance Prevention. *J. Cleaner Prod.* **2018**, *177*, 232−244.
(36) Schuh, G.; Schenk, M.; Servos, N. Design of a Simulation Model for the Assessment of a Real-Time Capable Disturbance Management in Manufacturing Supply Chains. *Procedia Manuf.* **2015**, *3*, 425−432.
(37) Guertler, B.; Spinler, S. Supply Risk Interrelationships and the Derivation of Key Supply Risk Indicators. *Technol. Forecast. Soc. Change* **2015**, *92*, 224−236.
(38) Ivanov, D.; Dolgui, A. OR-Methods for Coping with the Ripple Effect in Supply Chains during COVID-19 Pandemic: Managerial Insights and Research Implications. *Int. J. Prod. Econ.* **2021**, *232*, No. 107921.
(39) Singh, S.; Kumar, R.; Panchal, R.; Tiwari, M. K. Impact of COVID-19 on Logistics Systems and Disruptions in Food Supply Chain. *Int. J. Prod. Res.* **2021**, *59*, 1993−2008.
(40) Schmitt, A. J.; Singh, M. A Quantitative Analysis of Disruption Risk in a Multi-Echelon Supply Chain. *Int. J. Prod. Econ.* **2012**, *139*, 22−32.
(41) Schmitt, A. J.; Singh, M.Quantifying Supply Chain Disruption Risk Using Monte Carlo and Discrete-Event Simulation. In *Proceedings of the 2009 Winter Simulation Conference (WSC)*; 2009; pp. 1237−1248.
(42) Sahay, N.; Ierapetritou, M. Multienterprise Supply Chain: Simulation and Optimization. *AIChE J.* **2016**, *62*, 3392−3403.
(43) Barbati, M.; Bruno, G.; Genovese, A. Applications of Agent-Based Models for Optimization Problems: A Literature Review. *Expert Syst. Appl.* **2012**, *39*, 6020−6028.
(44) Otto, C.; Willner, S. N.; Wenzad, L.; Frielera, K.; Levermann, A. Modeling Loss-Propagation in the Global Supply Network: The Dynamic Agent-Based Model Acclimate. *J. Econ. Dyn. Control* **2017**, *83*, 232−269.
(45) Behdani, B.; Lukszo, Z.; Srinivasan, R. Agent-Oriented Simulation Framework for Handling Disruptions in Chemical Supply Chains. *Comput. Chem. Eng.* **2019**, *122*, 306−325.
(46) Ledwoch, A.; Yasarcan, H.; Brintrup, A. The Moderating Impact of Supply Network Topology on the Effectiveness of Risk Management. *Int. J. Prod. Econ.* **2018**, *197*, 13−26.
(47) Bugert, N.; Lasch, R. Supply Chain Disruption Models: A Critical Review. *Log. Res.* **2018**, *11*, 1−35.
(48) Küçükyavuz, S.; Sen, S.An Introduction to Two-Stage Stochastic Mixed-Integer Programming. In *The Operations Research Revolution*; Batta, R., Peng, J., Smith, J. C., Greenberg, H. J., Eds.; INFORMS, 2017; pp. 1−27.
(49) Gholami-Zanjani, S. M.; Jabalameli, M. S.; Klibi, W.; Pishvaee, M. S. A Robust Location-Inventory Model for Food Supply Chains Operating under Disruptions with Ripple Effects. *Int. J. Prod. Res.* **2021**, *59*, 301−324.
(50) De, A.; Mogale, D. G.; Zhang, M.; Pratap, S.; Kumar, S. K.; Huang, G. Q. Multi-Period Multi-Echelon Inventory Transportation Problem Considering Stakeholders Behavioural Tendencies. *Int. J. Prod. Econ.* **2020**, *225*, No. 107566.
(51) Iakovou, E.; Vlachos, D.; Xanthopoulos, A. A Stochastic Inventory Management Model for a Dual Sourcing Supply Chain with Disruptions. *Int. J. Syst. Sci.* **2010**, *41*, 315−324.
(52) Sawik, T. Integrated Selection of Suppliers and Scheduling of Customer Orders in the Presence of Supply Chain Disruption Risks. *Int. J. Prod. Res.* **2013**, *51*, 7006−7022.
(53) Sawik, T. A Portfolio Approach to Supply Chain Disruption Management. *Int. J. Prod. Res.* **2017**, *55*, 1970−1991.
(54) Sawik, T. On the Risk-Averse Optimization of Service Level in a Supply Chain under Disruption Risks. *Int. J. Prod. Res.* **2016**, *54*, 98−113.
(55) Sawik, T. On the Risk-Averse Selection of Resilient Multi-Tier Supply Portfolio. *Omega* **2021**, *101*, No. 102267.
(56) Sawik, T. Stochastic Optimization of Supply Chain Resilience under Ripple Effect: A COVID-19 Pandemic Related Study. *Omega* **2022**, *109*, No. 102596.
(57) Jahani, H.; Abbasi, B.; Hosseinifard, Z.; Fadaki, M.; Minas, J. P. Disruption Risk Management in Service-Level Agreements. *Int. J. Prod. Res.* **2021**, *59*, 226−244.
(58) Özçelik, G.; Faruk Yılmaz, Ö.; Betül Yeni, F. Robust Optimisation for Ripple Effect on Reverse Supply Chain: An Industrial Case Study. *Int. J. Prod. Res.* **2021**, *59*, 245−264.
(59) Hasani, A.; Khosrojerdi, A. Robust Global Supply Chain Network Design under Disruption and Uncertainty Considering Resilience Strategies: A Parallel Memetic Algorithm for a Real-Life Case Study. *Transport. Res. E: Log. Transport. Rev.* **2016**, *87*, 20−52.
(60) Lim, M. K.; Bassamboo, A.; Chopra, S.; Daskin, M. S. Facility Location Decisions with Random Disruptions and Imperfect Estimation. *Manuf. Serv. Oper. Manag* **2013**, *15*, 239−249.
(61) Rezapour, S.; Farahani, R. Z.; Pourakbar, M. Resilient Supply Chain Network Design under Competition: A Case Study. *Eur. J. Oper. Res.* **2017**, *259*, 1017−1035.
(62) Sadeghi, Z.; Boyer, O.; Sharifzadeh, S.; Saeidi, N. A Robust Mathematical Model for Sustainable and Resilient Supply Chain Network Design: Preparing a Supply Chain to Deal with Disruptions. *Complexity* **2021**, *2021*, No. e9975071.
(63) Azad, N.; Davoudpour, H.; Saharidis, G. K. D.; Shiripour, M. A New Model to Mitigating Random Disruption Risks of Facility and Transportation in Supply Chain Network Design. *Int. J. Adv. Manuf. Technol.* **2014**, *70*, 1757−1774.
(64) Baghalian, A.; Rezapour, S.; Farahani, R. Z. Robust Supply Chain Network Design with Service Level against Disruptions and Demand Uncertainties: A Real-Life Case. *Eur. J. Oper. Res.* **2013**, *227*, 199−215.
(65) Kamalahmadi, M.; Parast, M. M. A Review of the Literature on the Principles of Enterprise and Supply Chain Resilience: Major Findings and Directions for Future Research. *Int. J. Prod. Econ.* **2016**, *171*, 116−133.
(66) Kamalahmadi, M.; Parast, M. M. An Assessment of Supply Chain Disruption Mitigation Strategies. *Int. J. Prod. Econ.* **2017**, *184*, 210−230.
(67) Dolgui, A.; Ivanov, D. Ripple Effect and Supply Chain Disruption Management: New Trends and Research Directions. *Int. J. Prod. Res.* **2021**, *59*, 102−109.
(68) Cruise, J.; Flatley, L.; Gibbens, R.; Zachary, S. Control of Energy Storage with Market Impact: Lagrangian Approach and Horizons. *Oper. Res.* **2019**, *67*, 1−9.
(69) Subramanian, K.; Maravelias, C. T.; Rawlings, J. B. A State-Space Model for Chemical Production Scheduling. *Comput. Chem. Eng.* **2012**, *47*, 97−110.
(70) Kopanos, G. M.; Pistikopoulos, E. N. Reactive Scheduling by a Multiparametric Programming Rolling Horizon Framework: A Case of a Network of Combined Heat and Power Units. *Ind. Eng. Chem. Res.* **2014**, *53*, 4366−4386.
(71) Addis, B.; Carello, G.; Grosso, A.; Tànfani, E. Operating Room Scheduling and Rescheduling: A Rolling Horizon Approach. *Flex Serv. Manuf. J.* **2016**, *28*, 206−232.
(72) Li, Z.; Ierapetritou, M. G. Rolling Horizon Based Planning and Scheduling Integration with Production Capacity Consideration. *Chem. Eng. Sci.* **2010**, *65*, 5887−5900.
(73) Fattahi, M.; Govindan, K. Data-Driven Rolling Horizon Approach for Dynamic Design of Supply Chain Distribution Networks under Disruption and Demand Uncertainty: Data-Driven Rolling Horizon Approach for Dynamic Design of Supply Chain Networks. *Decis. Sci.* **2022**, *53*, 150.
(74) Fattahi, M.; Govindan, K. A Multi-Stage Stochastic Program for the Sustainable Design of Biofuel Supply Chain Networks under

Biomass Supply Uncertainty and Disruption Risk: A Real-Life Case Study. *Transport. Res. E Log. Transport. Rev.* **2018**, *118*, 534−567.
(75) Subramanian, K.; Rawlings, J. B.; Maravelias, C. T. Economic Model Predictive Control for Inventory Management in Supply Chains. *Comput. Chem. Eng.* **2014**, *64*, 71−80.
(76) Lejarza, F.; Baldea, M. Closed-Loop Optimal Operational Planning of Supply Chains with Fast Product Quality Dynamics. *Comput. Chem. Eng.* **2020**, *132*, No. 106594.
(77) Bhosekar, A.; Ierapetritou, M. A Framework for Supply Chain Optimization for Modular Manufacturing with Production Feasibility Analysis. *Comput. Chem. Eng.* **2021**, *145*, No. 107175.
(78) Brunaud, B.; Laínez-Aguirre, J. M.; Pinto, J. M.; Grossmann, I. E. Inventory Policies and Safety Stock Optimization for Supply Chain Planning. *AIChE J.* **2019**, *65*, 99−112.
(79) Cosma, O.; Pop, P.; Sabo, C. On the Two-Stage Supply Chain Network Design Problem with Risk-Pooling and Lead Times. *Cybern. Syst.* **2022**, 1−18.
(80) Spitter, J. M.; Hurkens, C. A. J.; de Kok, A. G.; Lenstra, J. K.; Negenman, E. G. Linear Programming Models with Planned Lead Times for Supply Chain Operations Planning. *Eur. J. Oper. Res.* **2005**, *163*, 706−720.
(81) Ogunnaike, B. A.*Random Phenomena: Fundamentals of Probability and Statistics for Engineers*; CRC Press: Boca Raton, 2014.
(82) Krishnan, V.*Probability and Random Processes; Wiley survival guides in engineering and science*; Wiley-Interscience: Hoboken, NJ, 2006.
(83) Allen, R. C.; Allaire, D.; El-Halwagi, M. M. Capacity Planning for Modular and Transportable Infrastructure for Shale Gas Production and Processing. *Ind. Eng. Chem. Res.* **2019**, *58*, 5887−5897.
(84) Allman, A.; Zhang, Q. Dynamic Location of Modular Manufacturing Facilities with Relocation of Individual Modules. *Eur. J. Oper. Res.* **2020**, *286*, 494−507.

https://doi.org/10.1021/acs.iecr.2c01641
Ind. Eng. Chem. Res. 2022, 61, 16747−16763