Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Simulation-based assessment of supply chain resilience with consideration of recovery strategies in the COVID-19 pandemic context

Javid Moosavi a, Seyedmohsen Hosseini b, *

a School of the Built Environment, University of Technology Sydney, Sydney, Australia
b Industrial Engineering Technology, University of Southern Mississippi, Long Beach, MS, USA

ARTICLE INFO
Keywords:
Supply chain resilience
Supply chain disruption
Supply chain risk management
Simulation
COVID-19

ABSTRACT
In the wake of the COVID-19 pandemic, many firms lacked a strategy to cope with disruptions and maintain resiliency. In this study, we develop a measurement method to evaluate the impact of resilience strategies in a multi-stage supply chain (SC) in the presence of a pandemic. For the first time, we propose a method to deduce quantitative resilience assessment from simulation. We implement two resilience strategies, i.e., prepositioning extra-inventory and a backup supplier, and then we simulate its impact on SC resilience and financial performance. The simulation results indicate that the extra inventory leads to a higher resilience than a backup supplier but costs more for the given contextual setting. Finally, we examine the demand fulfillment and observe that the extra-inventory strategy allows for a higher service level, confirming our resilience simulations. We discuss the managerial implications of these findings on the descriptive and predictive analysis levels. Decision-makers can utilize our model and findings to develop a response plan in the occurrence of a pandemic or any long-duration high magnitude disruption. Also, scholars and managers can use our proposed method to measure SC resiliency from simulation in any disruption.

1. Introduction

In this competitive world, modern SCs are designed to be efficient and effective. Supply chains are multi-tier complex chains of supply, which are distributed globally. Although these qualities enable the SC to work efficiently, it increases the SC’s vulnerability under the risks. Supply chain risks are categorized into two main types, such as operational and disruption risks (Chen et al., 2013). We focus on the disruption risks in this study. Notably, we study the ripple effect that refers to the propagation of disruption at one node toward the SC network’s multiple echelons (Ivanov et al., 2014). This section indicates the Covid-19 impact on the world. It specifies the disruption difference caused by the outbreak compared to the other disruptions and finally discusses the cost-efficient SC design versus the resilient SC.

The Covid-19 pandemic is a global tragedy, and its impact on the world is devastating. To date (May 10th, 2021), over 160 million people are infected, and 3.28 million have died. World Health Organization (WHO) declared a public health emergency in January 2020 and designated it as a pandemic in March 2020 after fast spread across 120 countries (WHO, 2020). Many countries mandated strict lockdowns and border closures to control the virus spread. More than 2.6 billion people were placed on in-home quarantine all over the world in March and April. The social and economic impact of the pandemic is catastrophic. World Bank Organization estimated that the pandemic would plunge most countries into recession in 2020 by 5 percent worldwide GDP shrink. Strict lockdowns and border closures resulted in severe SC disruption. Various industries’ SC, such as automotive, FMCG, food, and health industries, are affected significantly. Manufacturing SC is complicated, and the pandemic disruption significantly affected the SC financial and operational performance.

For example, the lack of a low-cost component in an automobile manufacturing site could stop the production line resulting in customer dissatisfaction and profit loss (Chirra & Kumar, 2018). China’s automobile export plunged to a financial record low by 80 percent due to decreased demand (Segal & Gerstel, 2020). Also, disruption in China’s automobile part exports resulted in large-scale car production disruption across Europe and assembly plant closure in the United States (Deloitte, 2020).

Likewise, the pandemic affected the food SC drastically, both financially and operationally. The sudden change in purchase patterns, i.e., panic buying and home cooking, resulted in the SC collapse (Hobbs, 2020). Besides, labor shortage, border closure, and logistic network
disruption affected the food SC significantly (Hobbs, 2020). Rizou et al. (2020) studied virus transmission through the food SC environment. The study indicates that the virus could spread by the SC network. Particularly, infection chances increase as we move from farm to fork because of more people (a potential source of infection) involved in the SC operation. The study proposed particular precautions for each SC operation stage to decrease the virus spread, such as social distancing, surface disinfection, and staying home if you are sick, affecting the SC operational performance.

The SC disruption arises from natural and human-made interruptions such as floods, earthquakes, terrorist attacks, and civil unrest. The Covid-19 pandemic impact is considerably different from the other SC disruptions in terms of magnitude and duration (Guan et al., 2020). Disruption magnitude refers to the scale of the disruption impact to related enterprises, and duration refers to the time that a disruption’s impact lasted on the SC. The scale and magnitude of the Covid-19 outbreak is catastrophic compared to the other experienced disruptions, namely, floods in China, earthquakes in Japan, and Tsunamis in Asia. The Covid-19 pandemic disruption propagated through all the SC enterprises and companies worldwide (Ivanov, 2020). Jewell et al. (2020) indicate the Covid-19 pandemic disruption on HIV-related death in sub-Saharan Africa, which could indicate the pandemic’s magnitude scale.

Furthermore, the duration of the pandemic is significantly different from the other disruptions. Despite natural disasters and terrorist attacks that do not last for the long term, it is predicted that the Covid-19 causes enormous long-term SC disruptions (Ivanov, 2020; Soreide et al., 2020).

Due to the devastating impact of the outbreak and recent SC collapses, SC resilience attracts scholars’ and managers’ attention. In today’s competitive world, SCs are designed to be efficient by employing lean approaches. The lean methodology, i.e., just-in-time and single-sourcing methods, contrasts to resilience methods, such as excess inventory and backup suppliers (Hosseini & Ivanov, 2020; Torabi et al., 2015). The COVID-19 outbreak caused catastrophic SC disruption and attracted attention to the importance of SC resilience. However, it is difficult to examine how to measure resiliency and evaluate resiliency strategies impact on SC performance. Therefore, we aim to address this objective by modeling the COVID-19 impact, analyzing resilience and financial performance using simulation technique. To address these objectives, this study attempts to answer the following questions:

RQ1. What is the impact of resilience strategies in a multi-stage SC in the presence of a pandemic?

RQ2. How to deduce quantitative resilience assessment from a simulation when resilience strategies are deployed?

This article is the first study that analyzes the impact of the resilience strategies in the occurrence of a high magnitude and prolonged duration disruption like the COVID-19 outbreak. However, this method could be used in any SC disruption risk characterized as high magnitude and long duration.

We set several experiments to simulate the resilience strategies on a real-world case study SC. By answering RQ1, we aim to analyze the recovery strategies’ impact on financial metrics, i.e., revenue, profit, cost, and demand fulfillment. Furthermore, this study develops a method for the first time that calculates SC resiliency based on simulation. Today’s SCs are very complex, and SC experts are using simulation to analyze the complex SCs operation. However, resilience measurements based on simulation are scarce. We aim to fill this gap by answering RQ2. This study contributes to the SC resiliency research by modeling the COVID-19 pandemic as a high magnitude and prolonged disruption. Furthermore, this study analyzes the impact of resiliency strategies, which has rarely been studied. Last but foremost, we develop a method to measure resiliency based on simulation. The simulation’s outcome could help evaluate the strategies’ consequences and select the best response plan before the next severe disruption. Policymakers could use the outcome of this research to develop response plans.

The research methodology diagram is illustrated in Fig. 1. As shown in Fig. 1, we review the pandemic, simulation, and resiliency literature (Section 2). After, we discuss the case study, model, and input parameters (Section 3). Later, we simulate two scenarios, i.e., a disrupted SC and a disruption-free scenario (Section 4). The disrupted scenario has two recovery plans, i.e., backup supplier and backup inventory. The simulation provides the financial performance, demand fulfillment and also furnishes resiliency measurement (Section 5). In particular, we obtain financial performance, resilience, and demand fulfillment of the recovery plans. Thereupon we compare them with the disruption-free scenario results, which furnishes managerial insights (Section 6). Finally, the study concludes the research in the last section (Section 7).

2. Literature review

We review the literature on SC and pandemic, simulation, and SC resilience. The following subsections review the methods and contributions of the studies. By the end of Section 2, we compare the closely related articles with this study.

2.1. Pandemic and SC management

Morens et al. (2009) introduced what a pandemic is and how to recognize an epidemic when it occurs. The study indicates that scientists and scholars have been focused on influenza. An influenza pandemic has occurred ten times in the past 300 years and killed hundreds of millions of people (Potter, 2001). The Spanish flu pandemic killed at least 50 million people worldwide between 1918 and 1920 (Osterholm, 2005). Therefore, before the Covid-19 pandemic, most of the pandemic literature focused on influenza, e.g., (Chick et al., 2008); however, it is expected that the current pandemic would change this trend (Vardeny et al., 2020). Queiroz et al. (2020) conduct a systematic literature review to identify epidemics in SC management. The study indicates approximately half of the studies were devoted to the Influenza epidemic (43.7%), following by epidemic control without focusing on a particular epidemic (18.5%). Then Cholera and Ebola by 12.5 %, followed by Covid-19 with less than 10 percent of the literature.

The study also designates that most of the studies proposed an optimization model for resource allocation, such as facility location, patient allocation, food, and medicament (e.g., vaccine) distribution. Due to the primary focus on optimization methods, most of the studies used mathematical approaches, e.g., linear programming (Liu et al., 2020, p. 1; Zucchi et al., 2020), game theory (Ivanov & Dolgui, 2020a; Shamsi Gamchi & Torabi, 2018), and few articles study case studies and simulation (Currie et al., 2020; Ivanov, 2020; Singh et al., 2020). Ivanov (2019) conducted a simulation analysis of SC design and production-ordering systems in SC disruption. The authors used a real-life case study to study the impact of severe disruption on production and distribution networks. It concludes with insight on the recovery policies for the post-disruption period. Singh et al. (2020) focused on the public distribution network and developed a simulation model with three scenarios to demonstrate disruption. The paper highlighted the importance of SC resilience during a pandemic and declared that the proposed model could enhance SC resilience by matching demand in a pandemic. The following subsection discusses the literature on resilient SC.

2.2. Supply chain simulation

We review the literature that simulates SC disruption and risk mitigation strategies. This section divided the simulation literature approaches into system dynamics, discrete-event, and hybrid simulation. Then investigate their results and contributions.

System dynamics is a simulation method to model the non-linear behaviour of a system. Dong (2006) aimed to analyze a disrupted SC by simulating the uncertainties associated with road networks. This
paper tested replenishment strategies and defined forecasting methods. The conclusions recommended that the replenishment solution is a two-stage decision. First, plan inventory strategy based on the shared information and then adjust it based on the fluctuation’s prediction. Notably, the Joint Order inventory strategy resulted in better performance.

Huang et al. (2012) studied two purchasing strategies: without backup supply and a contingent supplier to provide an extensive understanding of backup supply. The main finding is the duration of the retailer’s fluctuation is significantly more than the time of supply disruption. Moreover, the longer the supply disruption is, the heavier the fluctuation is.

Olivares-Aguila and ElMaraghy (2020) investigated the effect of partial and full disruptions on service level, cost, profit, and inventory level. Findings show that the upstream disruption has a significant impact on the performance elements compared to the downstream disruption.

Bueno-Solano and Cedillo-Campos (2014) investigated the propagation impact on the performance of the inventory level. The findings show that inventory level can soar to 600%.

Hilletofth et al. (2016) focused on the restoration and studied disruption on the three tiers such as producers, logistics, and demand. This paper recommended a different combination of collaboration strategies in various types of SC disruption.

Gu and Gao (2017) focused on manufacturing SC. This study suggests setting multi-echelon inventory levels before production disruption and a backup plan after disruption to match sales at the needed sales ratio. Similarly, Wang et al. (2014) studied backup suppliers and shed light on the backup purchasing strategy’s value.

Discrete-event simulation has been used continuously by researchers and practitioners for studying SC disruption in recent years. It provides a proper environment to evaluate different strategies and understand associated outcomes (Melnyk et al., 2009; Moosavi et al., 2021). Ivanov (2018) studied disruption propagation with the lens of sustainability. The results show that employers’ fortification in regions mitigates the ripple effect and enhances sustainability. Furthermore, the reduction of storage facilities increases sustainability but exacerbates the disruption effects. Similarly, Ivanov (2019) analyzed production ordering and shed light on recovery policies on a post-disruption time. This study’s main finding is that recovery policies should not be limited to only disruption.
time, and it should be extended to the post disruption period. Furthermore, it asserts that recovery policies should be considered in the SC design.

Likewise, Melnyk et al. (2009) endorsed that recovery policies should be structured in SC design. Schmitt and Singh (2009) focused on both supply disruption and demand uncertainties. This study shows how proactive planning reduces the impact of SC disruption.

Dolgui et al. (2018) observed the cause of the ripple effect and evaluated mitigation strategies, and presented a framework for controlling it. The main findings illustrated that single sourcing, low inventory, and non-reconfigurable production systems aggravate the impact. It concludes that the learnness and complexity of the SCs influence the control framework of the disruption.

Samvedi and Jain (2013) explored forecasting methods and analyzed the method’s performance to define which model performs better in disruption circumstances.

Hybrid simulation benefits from two or more methods. For example, Ivanov et al. (2016) implemented system dynamic and linear programming. The significance of this paper is the acknowledgment of service level and sales volumes as resilience indicators. Over again, Ivanov and Dolgui (2020b) utilized a combination of simulation, optimization, and data analytics to study the disruption risks. This study’s main conclusion is that digital technologies can reduce disruption risks by boosting demand responsiveness and enhancing capacity flexibility.

In summary, all the above approaches have been utilized in analyzing SC disruption and evaluating recovery policies. However, system dynamics and discrete event are more popular. Tako and Robinson (2018) discussed no significant differences between the system dynamic and discreet event in terms of results. Selecting one approach rather than the other depends on the field of the study and users. Our literature review indicates that outstanding studies have employed discreet event simulation for SC disruption and recovery policy evaluation (i.e. Aldrighetti et al., 2019; Hosseini et al., 2019; Ivanov, 2019, 2020; Ivanov & Dolgui, 2020b; Schmitt & Singh, 2009). Therefore, this study employs a discrete event simulation methodology to develop a simulation model using anyLogistix software (AnyLogistix, 2020).

2.3. Supply chain resilience assessment

Quantifying SC resilience is a critical issue. Hosseini et al. (2016) conducted a comprehensive study that reviews SC resilience definitions and quantification metrics. Most resilience studies use the resilience triangle introduced by Tierney and Bruneau (2007) to analyze disaster resilience loss (e.g., Rodríguez-Nikl, 2015; Zobel, 2010, 2011; Zobel & Khansa, 2014). It represents the measurement of functionality loss and its time for a system to return to an expected performance level (Falasca, 2008). Soni et al. (2014) quantified resilience by calculating a single numerical index to assess the effectiveness of risk mitigation strategies. They calculated the SC resilience index by quantification of resilience enablers and considering the resilience variable matrix. Then they compared the resilience index to develop a response plan. Hosseini and Ivanov (2019) proposed a Bayesian network approach to measure the resilience under the ripple effect in a car manufacturing supply chain. The introduced model could quantify suppliers’ resilience levels to provide a recommendation on controlling the ripple effect. While most studies focused on probability estimation, a few studies have studied the recovery-based approach to supply chain resilience quantification (Fattahi et al., 2020). Ivanov et al. (2016) proposed a method obtained from control theory to quantify resilience as a reaction to recovery control policy. They aimed to compute a schedule control policy and analyze its performance. The study proposed a scheduling model that takes recovery policies into action. Also, they suggested a resilience index attained from the notion of attainable set in control policy. Pavlov et al. (2017) used a genome method based on a probabilistic perspective to measure SC resilience and identify the critical suppliers. The authors considered both recovery and performance degradation to study the disruption propagation and quantify the structural robustness.

The method considers different disruption scenarios, e.g., ripple effect dispersal and recovery paths. Hosseini, Ivanov, and Dolgui (2020) modeled supplier disruption and its ripple effect by integrating Markov chain and Bayesian network approach. They proposed a metric to quantify the ripple effect in terms of total expected utility and service level. Behzadi et al. (2020) proposed an integrated metric including the multiple facets of time, cost, and the level of recovery to quantify the supply chain resilience. The metric assists in quantifying the net present value of profit loss. The study illustrates how different metrics could results in different decision in supply chain design hence it is critical to select the proper metric to model SC resilience.

Torabi et al. (2015) developed a resilience metric that is a function of different recovery strategies such as absorptive capacity (inventory prepositioning), adaptive capacity (backup supplier), and restorative capacity (restoration of disrupted supplier). The recovery strategies are titled $A$, $B$, and $C$, and the associated time of receiving items are represented by $LT_A$, $LT_B$, and $LT_C$, respectively. The authors considered the lost capacity recovered by each recovery strategy. Then they calculated the loss of resilience denoted by $RE$ with considering the lost capacities and associated time. Eq. (1) illustrates the resilience loss calculation.

$$RE = A \times LT_A + B \times LT_B + C \times LT_C$$

Then they calculate the resilience by Eq. (2):

$$RE = 1 - \frac{RE}{Q \times T}$$

where $Q$ is the total amount of items that the manufacturer requires and $T$ is the upper bound on the length of the recovery process.

Likewise, Ojha et al. (2018) proposed a resilience quantification metric calculated by service loss resulting from disruption. This study and Torabi et al. (2015) proposed a resilience measurement calculated by one (1) minus fraction of loss. Ojha et al. (2018) considered the loss of service level while Torabi et al. (2015) measure supplier capacity loss.

In this study, we use the proposed method by Torabi et al. (2015) to measure SC resilience based on simulation. We simulate the SC performance under different scenarios, and for the first time, we deduce quantitative resilience assessment from simulations.

To summarize, most of the pandemic literature is focused on influenza, while Covid-19 pandemic literature is scarce (Queiroz et al., 2020). Most of the studies focused on resource allocations, and SC disruption requires more investigations (Ivanov, 2020; Queiroz et al., 2020). Besides, simulation and case studies are increasingly utilized to study SC disruption in pandemics (Singh et al., 2020). Therefore, we aimed to bridge these gaps by using a case study simulation to analyze the impact of disruption and recovery strategies on SC performance. In the following, we compare the closely related studies discussed in the literature review with our research to illustrate this study’s novelty and contribution.

Table 1 signifies the six very closely related studies. Supply Chain disruption caused by COVID-19 is different from the previous pandemic regarding the high magnitude and long duration. Four closely relevant studies explore COVID-19 disruption, and three of them use simulation, only two of them measures resiliency, but none of them consider recovery strategies. This study is the only research conducting simulation-based research to measure resiliency considering recovery strategies in the context of the COVID-19 caused disruption. Torabi et al. (2015) measure resiliency with consideration of recovery strategies, but it implemented a mathematical model, which is challenging to utilize in a real-world complex SC operation. We aim to contribute to this issue by proposing an innovative model developed in the extension of their method. In particular, our study proposed a method to measure SC resiliency based on simulation. Therefore, to the best of our knowledge, this study is the only simulation-based research calculating SC resiliency considering recovery strategies in such a high magnitude long-duration.
SC disruption like the COVID-19 pandemic.

3. Problem statement and model

3.1. Problem statement

This study explores a real-world case study; it is an LED panel light manufacturing company located in Iran, Middle East, Asia. It has a three-echelon SC, including suppliers, factory facility, and customers. The LED manufacturing company located in a city named Zanjan in the northwest of Iran with a supplier in Shenzhen (China), a local back up supplier in Zanjan (Iran), a factory facility in Zanjan, and five customers in the capital city of Tehran, 340 km of the south-east. As the SC structure is demonstrated in Fig. 2; the company procures electronic boards and LED components from a supplier in Shenzhen. These electronic parts were sent to Iran from China. The components are collected in an airport located 350 km away from the manufacturing site and sent to the manufacturing site. The pieces assemble at the manufacturing site and are sent to customers.

The following statements have been considered to model the disruption. The duration of the experiment is one year. The inventory control policy is s, S method (for more, see Bashyam & Fu, 1998; Veinott & Wagner, 1965), and less-than-truckload (LTL) shipments are allowed in the logistic system. Transportation costs are computed based on the

### Table 1
The closely related studies.

| Author(s)       | Disruption Cause | Modeling Approach | Modeling Approaches                     | Vulnerability Type | Recovery Strategies | Resiliency Measurement | Contribution and Findings                                                                 |
|-----------------|------------------|-------------------|-----------------------------------------|--------------------|---------------------|------------------------|----------------------------------------------------------------------------------------|
| Singh et al.    | COVID-19         | Simulation        | Discrete-Event                          | Warehouse          | –                   | –                      | Integration of backup warehouse contributed to the SC performance.                      |
| (2020)          |                  |                   |                                         |                    |                     |                        |                                                                                         |
| Ivanov (2020)   | COVID-19         | Simulation        | Discrete-Event                          | Supply, Logistic and Demand | –                   | –                      | Opening and closing time of facilities have a major impact on SC performance in the pandemic outbreak. |
| Currie et al.   | COVID-19         | Simulation        | Distributed Simulation                  | Supplier           | –                   | –                      | Different decisions making should have different modeling, i.e., epidemiologic modeling should feed operational modeling. |
| (2020)          |                  |                   |                                         | Disruption         |                     |                        |                                                                                         |
| Torabi et al.   | Any Disruption   | Mathematical      | Stochastic Programming Dynamic Game-Theoretic | Supplier Selection | –                   | –                      | Viability is different than resiliency, and it is a necessary quality to be added to the SC resilience analysis |
| (2015)          |                  |                   |                                         | Disruption         |                     |                        |                                                                                         |
| Ivanov and      | COVID-19         | Mathematical      | SIR Epidemiology Compartmental Model    | Manufacturer       | –                   | –                      | Production risks taken by vaccine manufacturers resulted in insufficient vaccine supply. A cost-sharing contract contributes to that matter. |
| Dolgui (2020a)  |                  |                   |                                         | Disruption         |                     |                        |                                                                                         |
| Chick et al.    | Influenza        | Mathematical      | SIR Epidemiology Compartmental Model    | Manufacturer       | –                   | –                      |                                                                                         |
| (2008)          |                  |                   |                                         | Disruption         |                     |                        |                                                                                         |
| Hosseini,       | Any Disruption   | Simulation        | Discrete-Event                          | Supplier           | –                   | –                      | Identifying vulnerable suppliers whose disruption have a higher impact on downstream entities |
| Ivanov, and     |                  |                   |                                         | Disruption         |                     |                        |                                                                                         |
| Dolgui (2020)   |                  |                   |                                         |                     |                     |                        |                                                                                         |

*Fig. 2. The configuration of supply chain studies in this paper.*
size, weight, and shipment distance. All the other costs, such as fixed, inventory, and production costs, are known and will employ in the simulation. Furthermore, the time of the shipments, production, and lead times are known. The company produces two products; however, we study only one (A9) to simplify the model.

3.2. Model and assumptions

We developed a discrete-event simulation model using anyLogistix software. anyLogistix is a software that provides SC simulation and optimization, allowing for an integrated model of SC analysis under disruptions (Aldrighetti et al., 2019; Ivanov, 2019; Singh et al., 2020).

Since the COVID-19 pandemic is an extraordinary kind of disruption, i.e., a long-term SC crisis or a super disruption, we address these specifics in our simulation model. First, the pandemic resulted in a very long disruption (Sareide et al., 2020). Second, its magnitude is catastrophic (Singh et al., 2020). The pandemic is formed by disruptions at several SC echelons (Ivanov, 2020). In our model, we consider disruptions at both primary supplier and manufacturer. Third, the pandemic disruption begins and ends gradually (unlike instantaneous events). As such, the firms have time to preposition inventory in the wake of a pandemic and activate a backup source. Our model utilizes these specifics when planning and deploying recovery strategies.

As Fig. 3 demonstrates the simulation model, we simulate the pandemic, SC operation, and recovery dynamics. Pandemic dynamic, including the supplier and manufacturing disruption, is simulated by the software’s option titled “Event.” This icon allows opening and closing facilities and production lines at a particular time. We model the pandemic dynamic by closing the facility on the dates demonstrated in Fig. 5.

To simulate recovery dynamics, we develop two recovery scenarios; backup inventory (prepositioned inventory) and backup supplier. For the backup inventory scenario, we set two inventory levels and associated prices. Then we run the experiment one time with the first inventory data set and one time with the other inventory data set. To simulate the backup supplier, we develop two different experiment runs; Chinese and local suppliers. We use the software edition that allows making three different suppliers. We set the Chinese and local suppliers with their associated locations, prices, transportations, and fees. Then we implement two different experiment runs; with the Chinese supplier data setting then the local supplier. Regarding simulating operation dynamics, we set supply/demand data, facility locations, customer details, transportation costs, and paths that will be discussed in the following.

Backup supplier- Cooperation with a backup supplier is a valuable resilience and response strategy during supply chain disruption (Hosseini & Ivanov, 2020; Yin & Wang, 2018). A reliable backup supplier has been used to replenish the inventory (Chen et al., 2013). The backup supplier is set to operate in unplanned situations; accordingly, the capacity, time, and cost are reasonably different from the regular supplier (J. Chen et al., 2013; Hou et al., 2017), so it requires an analysis of how it affects the KPIs (Ivanov, 2017). Accordingly, we implement the following experiment in the next section to simulate how the local backup supplier impacts the SC. The local supplier’s time and cost are also employed in the experiment to evaluate the backup supplier’s financial and customer performance.

Back up inventory- Managers have been implemented high inventory levels to mitigate the effect of disruption (Atan & Snyder, 2012; Christopher & Lee, 2004). Although it is associated with higher total costs such as financial, material and holding costs (Zhou & Yang, 2003), it is still necessary to replenish the inventory during disruption time (Löcker et al., 2019). Hence, we conducted a simulation experiment to study the impact of the higher inventory level on the company’s performance in the next section. In particular, the inventory level is changed to evaluate the performances.

Further, our simulation model builds on the following assumptions and input data:

Structural dynamics- According to Fig. 2, SC’s structure includes the overseas supplier, local backup supplier, manufacturing facility, and five customers. As illustrated in Fig. 5, China’s supplier stop in the first quarter of the year, and the SC structure changes from the overseas supplier to the local supplier. Also, prepositioned inventory is activated throughout the timeline. So the SC operation is changing throughout time.

Supply- The SC benefits from supply from overseas suppliers due to the competitive prices. However, the company set a local backup supplier in case of a supply disruption. The local supplier offers higher prices than the Chinese supplier, but it is located close to the manufacturing facility and could eliminate the risk of global disruption.

Customer- the company has five customers located in a capital city named Tehran, 365 Kilometers from the factory site in Zanjan.

Facility- the only facility in the supply chain model is the factory plant located in Zanjan.

Locations- the simulation has eight different locations. Five locations are for five different customers; one is for the factory facility, one supplier is located in China, and one local supplier near Tehran.
Paths- the supply chain has seven paths—five paths from the factory to the customers and two paths from suppliers to the factory. Fig. 4 demonstrates Chinese supplier location in Shenzhen, Iranian supplier in Zanjan, factory facility in Zanjan, and customers’ locations in Tehran. Transportation costs from the factory to the customers are calculated by one dollar per product drop. Similarly, the cost of aluminum transportation from the supplier to the factory is one dollar per drop.

Demand- Our demand follows a triangle distribution, widely used in the business simulation (Fairchild et al., 2016). It is a suitable approach to consider uncertainty by providing minimum, mode, and maximum values. The “Min” is the minimum number of products ordered by each customer, “Mode” is the most likely demand, and “Max” is the maximum number of products. Finally, the predicted (expected) demand is used as demand data in simulation. The predicted demand is calculated as represented in Eq. (3).

\[
\text{Min} + 4 \times (\text{Mode}) + \text{Max} \\
6
\]

Table 2, illustrates the customers’ minimum, mode, maximum, and calculated predicted (expected) demand.

Inventory- The Company uses (s, S) inventory control policy. This approach is an order-up-to-policy, also known as the min/max method. The ‘s’ is the order point, and ‘S’ is the order up to level (Caplin, 1985; Chen et al., 2006; Perera et al., 2018).

The “s, S” amounts are not optimal numbers; due to the several procurement difficulties that the company faces, they use s = 1 and S = 15.

Transportation - The products are transported in LTL shipping, and the paths are the real paths. The transportation costs are calculated as X (0.3) \times \text{weight} \times \text{distance}.

KPIs- Defining the right KPIs will assist in an in-depth business performance evaluation (Cai et al., 2009; Parmenter, 2015). This study intended to investigate what happened during the Covid-19 pandemic on this company and evaluates the potential strategies for the future. Accordingly, the number of sales, profit, and total costs are the main KPIs in this simulation. Aldrighetti et al. in (2019) pursued a three-dimension model for evaluating performance, including financial, customer, and operational performance, which is endorsed by Ivanov (2017). Likewise, we utilize financial performance and demand fulfillment to set the KPIs.

Ripple effect- Ivanov (2017) analyzes a ripple effect in a manufacturing company started from an overseas supplier and propagate through the next stages. Dolgui et al. (2018) studied disruption propagation on supply chain performance to develop response plans. Likewise, this study analyzes a ripple effect in a multi-echelon manufacturing supply chain disruption that started from an overseas

Table 2

| Customer ID | Min | Mode | Max | Predicted Order |
|-------------|-----|------|-----|-----------------|
| Customer 1  | 30  | 35   | 40  | 35              |
| Customer 2  | 3   | 7    | 11  | 7               |
| Customer 3  | 3   | 7    | 11  | 7               |
| Customer 4  | 10  | 14   | 18  | 14              |
| Customer 5  | 3   | 7    | 11  | 7               |

Fig. 4. Chinese supplier, local supplier, factory, and customers' locations and paths.
supplier and impacts the other stages. This model is unique because the COVID-19 intensity is significantly unusual regarding the magnitude and duration. The previously experienced disruptions e.g., floods and earthquakes, happens in a geographical area, but the COVID-19 affected the entire world. Also, this pandemic resulted in border closure which does not usually occur in the other types of disruptions. Disruption time is exceptionally long; many countries worldwide are experiencing an outbreak far beyond one year now since the pandemic started. Therefore, this simulation model is different regarding the disruption magnitude and time.

Also, the SC structure is different because the backup supplier is located in the country rather than another supplier located in Asia. In addition, we do not have a distribution center, and all the products are sent directly to the customers.

4. Experiment

Fig. 5 demonstrates the experiment timeline and related dates. The disruption triggers are the Supplier stop in China on 28/3/2020, and the production line stops at the manufacturer on 28/5/2020 due to the lack of material supply. The company classifies the state of their operations as a “disruption” if the on-time delivery (i.e., service level) indicator drops below 70%, and the operations are recovered if the service level exceeds 80%. Two SC recovery strategies are considered: (a) prepositioning of extra-inventory before disruption and (b) activation of a backup supplier in case of disruption. Both strategies are considered before the disruption as a proactive plan. The strategies would be employed when a disruption happens. The extra-inventory and local supplier strategy activates on the supply run-out date (28/5/2020).

4.1. Disruption-free scenario

All the required data, such as demand, inventory and transportation, is set as discussed in the previous section. The “failure service level” is set at 70%, and the “recovery service level” is assigned at 80%. Examination’s start day is set on the first day of 2020, and the experiment moves toward the last day of the year.

4.2. Disrupted scenario recovered by backup supplier

All the settings and data are the same as the disruption-free procedure, except “Event” provided by the software to implement operation circumstances such as disruption. We employed two events to simulate the disruption. First is the Chinese supplier stops on 28/3/2020, and the second is the production line stops on 28/5/2020 due to the lack of material supply.

4.3. Disrupted scenario recovered by backup inventory

All the data is the same as the disruption-free procedure, and the disruption setting is the same as the previous scenario, but the inventory level is enhanced instead of altering the supplier.

4.4. Resilience measurement

Resilience measurement of an SC with a ripple effect considering both disruption and recovery policies is challenging and scarce (Hosseini & Ivanov, 2019). We use the resilience measurement method proposed by Torabi et al. (2015). It is a proper resilient measurement method to calculate the resilient level under disruption risks (Dolgui et al., 2018; Hosseini & Ivanov, 2020). The resilience is calculated by the amount of the items that the receiver party will not receive without considering the recovery plans, also known as the loss of resilience. The resilience loss calculated by the shortage of items multiplies by the associated lead time, as shown in Fig. 6. The vertical axis denotes the number of items, and the horizontal axis indicates the times it takes to deliver the items. The resilience loss and resilience represented by $\rho$ and $\Psi$ respectively, are calculated by Eqs. (4) and (5):

$$\rho = (A \times T_A) + (B \times T_B) + (C \times T_C),$$

(4)

$$\Psi = 1 - \frac{\rho}{T \times Q}$$

(5)

Fig. 6. The representation of loss and recovery of items (Torabi et al., 2015).
where \( T \) and \( Q \) denote the expected length of recovery and amount of items, respectively. \( A, B, \) and \( C \) are the recovered items due to implementing recovery strategies, and finally \( T_A, T_B, \) and \( T_C \) are waiting time to recover the recovery strategies as shown in Fig. 6.

Section 5.2 demonstrates the resilience calculation in further detail.

5. Simulation results

The objective is to identify the impact on overall financial and customer performance also measure resilience. Therefore we select profit, revenue, and the total cost to evaluate financial performance (Section 5.1) and demand fulfillment to calculate resilience (Section 5.2). All the simulations and measurements are employed under the free-disruption scenario as a baseline and disrupted SC, and then we analyze the performance of SC with recovery strategies.

5.1. Financial performance

We selected profit, revenue, and total cost to evaluate financial performance. First, the experiment was conducted in a normal operation and then under the disrupted scenario.

The normal profit, revenue, and total cost are illustrated in Fig. 7. The vertical axis is the monetary indicator, and the horizontal axis is the time in terms of days. Revenue and total costs started at zero and increased throughout the year. The increasing trend of revenue and the total cost keeps the profit line in a similar periodic shape. The total cost increased throughout the year. The increasing trend of revenue and the total cost affects the profit significantly.

As discussed in the introduction, this study calculates resilience based on the measurement method introduced by Torabi et al. (2015). Fig. 13 represents the disruption occurrence, and Fig. 14 illustrates the sale loss under disruption. We outline the sale loss by four areas, including \( A, B, C, \) and \( D \), to calculate the resilience loss by Eq. (2), where \( LT \) is the lead time. Eqs. (6) and (7) represent the calculation of the resilience loss.

\[
\rho = A \times LT_A + B \times LT_B + C \times LT_C + D \times LT_D
\]  
(6)

5.2. Resilience performance

We aimed to explore what is the impact of inventory level on the total cost. We employ “s” to the minimum acceptable level and \( S \) to the maximum and run the variation experiment. The experiment ran 431 iterations; varied a minimum of 0 to 100 and a maximum of 0 to 490. Table 3 and Fig. 12 reflect how different inventory level values impact the financial parameters. The optimum level is the minimum of 0 and the maximum of 100, while the worst arrangement is the min of 0 and the maximum of 490. Therefore, we can see that different inventory levels could cost up to 10% more.

Fig. 7. Financial performance in the disruption-free scenario.
The X-axis is the number of products, and the X-axis dimension of A, B, C, and D are all equal to 30. So the resilience loss can be calculated as shown in Eq. (8):

\[ \rho = 30 \times (232 - 203) + 30 \times (262 - 232) + 30 \times (275 - 262) = 3000 \]  

Eq. (8)

When the excess inventory strategy is employed, SC’s resilience can be calculated by Eq. (6). As shown in Fig. 15, \( T(100) \) is the total time started at day 175th to 275th, and \( Q \) is the total product amount from day 175th (290) to 275th (500). Specifically, the X-axis of area A is 290, and area D is 500. Eq. (9) represents resilience calculation under backup inventory experiment.

\[ \Psi = 1 - \frac{\rho}{T \times Q} = 1 - \frac{3000}{100 \times (500 - 290)} = 0.8572 \]  

Eq. (9)

According to Eq. (10), under the backup supplier plan, resilience is 0.7272.

\[ \Psi = 1 - \frac{3000}{100 \times (250 - 140)} = 0.7272 \]  

Eq. (10)

SC’s resilience is 85.72% when the company utilizes excess inventory strategy, while resilience is 72.72% when it employs the backup supplier. The results imply that SC is more resilient under using excessive

---

**Fig. 8.** Financial performance in the disrupted scenario.

**Fig. 9.** Financial performance in free disruption and disrupted scenarios.
inventory strategy than backup suppliers. However, the financial performance outperforms under backup suppliers compared to the excessive inventory.

In short, the resilience under the backup inventory and the backup supplier is 0.8572 and 0.7272, respectively; the SC is 13 percent more resilient under excessive inventory compared to local backup suppliers.
5.3. Demand fulfillment

We aimed to analyze the demand fulfillment performance in the disruption-free and disrupted supply chain operation and then employ the recovery policies and evaluate the demand fulfillment supported by them.

Fig. 17 illustrates the demand fulfillment in disruption-free and disrupted scenarios. The vertical and horizontal axis represents the number of delivered products and time unit (days), respectively. Due to material supply disruption, the ripple effect affects the supply chain on day 175, and the demand fulfillment causes concern. To evaluate the demand fulfillment, we utilized a tool in anyLogistix that computes the number of products delivered on time within the expected lead time.

Fig. 18 demonstrates the demand fulfillment supported by backup inventory and backup supplier. The vertical axis represents the number of delivered items, and the horizontal axis is the time in terms of days. Fig. 18 shows that the demand fulfillment by employing excess inventory is significantly superior to the backup supplier.

The demand fulfillment results support the resilience calculation; the excess inventory is superior to the backup supplier regarding delivering more products.

In summary, the company is more resilient, less profitable under the excessive inventory plan, and more profitable, less resilient under backup supplier.

6. Managerial insights

During the Covid-19 pandemic, SC becomes the lifeline of humanity. Supply chain resiliency attracts not only SC experts’ attention but also governments and policymakers. It is vital for authorities to strengthen robust SC resiliency of national security industries or medical countermeasures, e.g., vaccine, ventilator, and PPE (Simchi-Levi & Simchi-Levi,
Fig. 15. Excessive inventory recovery.

Fig. 16. Back up supplier recovery.

Fig. 17. Demand fulfillment in the free-disruption and disrupted scenarios.
To improve resiliency, measuring resiliency and the impact of recovery strategies on resiliency is crucial (Carvalho et al., 2012). This study conducted experiments based on a unique method for evaluating SC resiliency and financial performance, which indicates the following insights:

Insight 1: the holding prepositioned inventory is very costly, while it does not considerably increase resiliency. Fig. 10 signifies the costs and resiliency of backup inventory. The results reveal that the costs are considerably (approximately sixty percent) more than the backup supplier while the demand fulfillment is increased by 13%. In today’s competitive world, there is a low probability that companies prefer to pay the considerable price of prepositioning inventory to increase resiliency slightly. Furthermore, the likelihood of a significant disruption such as pandemic and natural disaster is low, so securing backup inventory for such a low probable risk is questionable.

Insight 2: inventory control policy could impact the financial performance significantly; therefore, managers should evaluate the inventory level impact on the SC to identify the optimal control policy under disruption. The variation analysis results indicate that a non-optimal inventory level could cost up to 10% more.

Insight 3: local suppliers could maintain the resiliency considerably at a reasonable cost. This study’s results indicate that a local backup supplier could maintain resiliency at an acceptable level at approximately 40% less cost than backup inventory. However, in some industries, such as national security industries or medical countermeasures, increasing resiliency even slightly is highly desirable rather than cost efficiency. Accordingly, decision-makers might develop their response plans in those situations, resilient as much as possible rather than cost-efficient.

In summary, this study’s analysis indicates that a backup inventory could provide slightly higher resiliency but costs significantly more than a backup supplier. Decision-makers could benefit from the indicated insights depending on the desired level of efficiency and resiliency that they are pursued.

7. Conclusion

The COVID-19 pandemic resulted in SC collapse in the entire world, which confirms that today’s complex and lean SC design is vulnerable to severe disruption. The COVID-19 outbreak attracts SC professionals and policymakers’ attention to enhancing SC resiliency besides efficiency. However, computing today’s complex SC resiliency is challenging. Measuring SC resiliency is a critical path to preparing a proactive plan for the next severe disruption. Supply chain scholars and practitioners employ simulation to analyze complex SC operations. Simulation provides multiple runs and experiments to study model sensitivity to different scenarios and variables. However, computing SC resiliency based on simulation is scarce. This study developed a method to measure SC resiliency based on simulation. We simulate an LED light manufacturing company in Iran, with a primary supplier in China and a local backup supplier. This study modeled two resilience strategies, i.e., backup supplier and backup inventory, under normal operation and pandemic scenarios. Then, we analyze the financial and resilience performance of two resilience strategies under the pandemic and compare them to a normal SC operation.

The results indicate that backup inventory results in 13% more resiliency but up to 60% more costs. The backup supplier’s financial performance is promising, with slightly less resiliency.

Two practical contributions emerge from this study, first scholars and managers can use the proposed method for measuring resiliency based on simulation. Second, the results could be used to develop response, and resiliency plans dependant on the expected level of resiliency and financial performance. The results reveal that proposition inventory resulted in a slightly higher resiliency with exceedingly higher costs. However, in some critical product supply, e.g., medical countermeasures enhancing resiliency even slightly is vital. Therefore, policymakers and governments might prefer to secure a backup inventory for essential products. But products with less importance of resiliency could organize a backup supplier in their country or geographical region, providing an acceptable level of resiliency with reasonable costs than backup inventory.

This study has a few limitations. First, we consider the disruption only on supply and eliminate the market demand’s change. The global pandemic makes fluctuations in demand and also could result in demand fluctuations. Future research could consider disruption in both the demand and supply. The second limitation is predicting a disruption’s occurrence probability and its impacts on proactive plans. Predicting a worldwide outbreak’s occurrence and scale is very difficult; significantly affecting the optimum level of excess inventory and backup supplier selection. Future research could study disruption occurrence probability and its impact on resiliency strategies.

The results show that the company is more profitable with the backup supplier, but it is more resilient with the backup inventory. This study concludes that post-COVID-19 SC design would be the intersection and integration of profitability and resiliency.

CRedit authorship contribution statement

Javid Moosavi: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – editing. Seyedmohsen Hosseini: Conceptualization, Formal analysis, Methodology, Visualization, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence
Soni, U., Jain, V., & Kumar, S. (2014). Measuring supply chain resilience using a grey approach for forecasting in a supply chain during intermittently disruptions. Engineering Applications of Artificial Intelligence, 26(3), 1044-1051. https://doi.org/10.1016/j.engappai.2012.12.002

Schmitt, A. J., & Singh, M. (2009). Quantifying supply chain disruption risk using Monte Carlo and discrete-event simulation. In Proceedings of the 2009 Winter Simulation Conference (WSC) (pp. 1237–1248). https://doi.org/10.1109/WSC.2009.5429561

Segal, S., & Gerstel, D. (2020). The Global Economic Impacts of Covid-19. https://www.csis.org/analysis/global-economic-impacts-covid-19

Shamsi Ganchi, N., & Torabi, A. (2018). Application of option contract in Epidemic control using vaccination. Advances in Industrial Engineering, 52(4), 609–620. https://doi.org/10.22059/jie.2019.247658.1495

Simchi-Levi, D., & Simchi-Levi, E. (2020). We need a stress test for critical supply chains. Harvard Business Review. https://hbr.org/2020/04/we-need-a-stress-test-for-critical-supply-chains

Singh, S., Kumar, R., Panchal, R., & Tiwari, M. K. (2020). Impact of COVID-19 on logistics systems and disruptions in food supply chain. International Journal of Production Research, 1–16. https://doi.org/10.1080/00207543.2020.1792000

Sonu, U., Jain, V., & Kumar, S. (2014). Measuring supply chain resilience using a deterministic modeling approach. Computers & Industrial Engineering, 74, 11-25. https://doi.org/10.1016/j.cie.2014.04.019

Sereide, K., Hallet, J., Matthews, J. B., Schnitzbauer, A. A., Line, P. D., Lai, P. B. S., Otero, J., Callegaro, D., Warner, S. G., Baxter, N. N., Teh, C. S. C., Ng-Kamstra, J., Meares, J. G., Hagander, L., & Lorenzon, L. (2020). Immediate and long-term impact of the COVID-19 pandemic on delivery of surgical services. The British Journal of Surgery. https://doi.org/10.1002/bjs.11670

Souza, V. D., Bloemhof-Ruwaard, J., & Borsato, M. (2019). Exploring ecosystem network analysis to balance resilience and performance in sustainable supply chain design. International Journal of Advanced Operations Management, 11(1–2), 26–45. https://doi.org/10.1504/IJAOM.2019.098525

Tako, A. A., & Robinson, S. (2018). Comparing discrete-event simulation and system dynamics: Users’ perceptions. In M. Kunc (Ed.), System dynamics: Soft and hard operational research (pp. 261–299). Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-95257-1_9

Tierney, K., & Bruneau, M. (2007). Conceptualizing and measuring resilience: A key to disaster loss reduction. TR News, 250. https://tid.trb.org/view/81.3539

Torabi, S. A., Bagherad, M., & Mansouri, S. A. (2015). Resilient supplier selection and order allocation under operational and disruption risks. Transportation Research Part E: Logistics and Transportation Review, 79, 22–48. https://doi.org/10.1016/j.tre.2015.03.005

Vardeny, O., Madjid, M., & Solomon, S. D. (2020). Applying the lessons of influenza to COVID-19 during a time of uncertainty. Circulation, 141(21), 1667–1669. https://doi.org/10.1161/CIRCULATIONAHA.120.046837

Veinott, A. F., & Wagner, H. M. (1965). Computing optimal (s, S) inventory policies. Management Science, 11(5), 525–552. https://doi.org/10.1287/mnsc.11.5.525

Wang, Y., Huang, M., & Chen, J. (2014). System dynamics modeling of backup purchasing strategies under supply disruption risks. International Journal of U and e-Service, Science and Technology, 7(6), 287–296.

WHO (2020). WHO Director-General’s opening remarks at the media briefing on COVID-19—15 April 2020. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—15-april-2020

Yin, Z., & Wang, C. (2018). Strategic cooperation with a backup supplier for the mitigation of supply disruptions. International Journal of Production Research, 56(12), 4306–4312. https://doi.org/10.1080/00207543.2017.1410246

Zhou, Y.-W., & Yang, S.-L. (2003). An optimal replenishment policy for items with inventory-level-dependent demand and fixed lifetime under the LIFO policy. Journal of the Operational Research Society, 54(6), 585–593. https://doi.org/10.1057/palgrave.jors.2604882

Zobel, C. W. (2011). Representing perceived tradeoffs in defining disaster resilience. Decision Support Systems, 50(2), 394–403. https://doi.org/10.1016/j.dss.2010.08.001

Zobel, C. W., & Khansa, L. (2014). Characterizing multi-event disaster resilience. Computers & Operations Research, 42, 83–94. https://doi.org/10.1016/j.cor.2011.09.024

Zucchi, G., Iori, M., & Subramanian, A. (2020). Personnel scheduling during Covid-19 pandemic. Optimization Letters. https://doi.org/10.1007/s11590-020-01648-2