



Modelling disruption ripple effect in the three-stage supply chain

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Abstract

A major disruption in the supply chain causes a shutdown or reduction in capacity. A disruption at any point in the supply chain spreads as a ripple effect to other members, causes a reduction or interruption in production and makes distributors unable to respond to customers with a lack of inventory or affects the lead time. The present research introduces and quantitatively shows the ripple effect of the disruption of the supply chain. To describe supply chain recovery and vulnerability, we integrated a discrete-time Markov chain with a Bayesian network model for simulating the propagation behaviour of supply chain interruptions. After that, we provided a set of standards for estimating the knock-on effects of a supply disruption on the supplier manufacturer and distributor in terms of delivery lead time and revenue loss. We made a comparison between the results of the manufacturer disruption and the supplier disruption. Results indicate that this model can show the result of disruption and high-risk paths in the supply chain so that we can estimate the supply chain vulnerability before disruption. If a disruption occurs at one point in the supply chain, other members will be subject to disruption, and each member closer to the disruption point will receive a larger blast wave. The novelty of the present study is the quantitative estimation of the risk of a long-time disruption ripple effect based on the lead time and lost sales for a three-tier supply chain and compared the ripple effect of the manufacturer disruption with the ripple effect of the supplier disruption.

Keywords: Markov Chain, Dynamic Bayesian network, Supply chain disruption, Covid-19, Ripple effect

Paper Type: Original Research

1. Introduction

Many factors and disruptions negatively affect the supply chain performance. One of these factors that affect supply chains and the business market today is the prevalence of Covid-19. One of the low-probability, high-impact disruptions that posed a major threat to the continuity of business and supply chains was the pandemic's outbreak at the end of 2019 in China and its expansion to other nations or completely disrupted many local and global production and support operations and has put supply chains at risk of a ripple effect. This pandemic created unanticipated vulnerabilities in several industries and services, including the automobile, semiconductor, food, and health sectors. Even if the Covid-19 outbreak has caused harm to people before, supply chains (SCs) and their managers have not experienced a problem of this size in decades (Ivanov & Dolgui, 2021a). Despite the fact that most businesses were aware of the pandemic's severe and detrimental consequences on their SC performance, the majority lacked a strategy and guidelines for modelling SC interruptions under pandemic circumstances (Ivanov, 2021a, 2021b). The pandemic prevalence was a first-of-its-kind instance of low-frequency disturbance risk with substantial uncertainty that affects a SC's operating activities in a serious and long-lasting manner. Separately or concurrently, SCs encountered serious vulnerabilities at the service level, delivery time, SC interruption, and demand variations. The standard delivery time for imports in Asian countries is not less than two times as long as ordinary operations in April 2020, according to the Institute for Supply Chain Management (ISM) (222% for China, 217% for South Korea, and 200% for Japan). Compared to other disruptive risks, COVID-19 can be distinguished (Ivanov, 2020a; Queiroz et al., 2020). The COVID-19 outbreak has affected many enterprises globally, in contrast to previous disruption risks. In addition, in contrast to other known disruptions, which never damage the SC more than once before recovery begins, the COVID-19 prevalence had a protracted duration and unprecedentedly wide-ranging effects that required the use of recovery treatments and created a cascade (Burgos & Ivanov, 2021; Ivanov, 2020b; Li et al., 2021; Ruel et al., 2021). The potential for structural disruptions and their knock-on effects is one of the major problems SC managements must deal with (Dolgui et al., 2018; Ivanov, 2017). The effect of ripples occurs

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when the influence of disturbance on upstream elements (i.e., suppliers, manufacturers) is not localized or consumed locally and spreads to downstream elements, according to Hosseini et al. (2020), Hosseini and Ivanov (2019), Kinra et al. (2020), Ozcelik et al. (2021), Dolgui et al. (2018, 2020), and other researchers. The term "ripple effect" describes how a disturbance in the SC spreads and how it affects the output performance of the SC (such as sales, on-time deliveries, and profit). It might potentially have negative effects that are more severe than a decline in performance during the short term. It can lead to a loss of market share. Following SC phases may experience material loss and decreased output due to lost capabilities or inventory as a result of a disrupted facility (Ivanov, 2018). Suppliers are essential to the SC. SC interruptions will have significant effects. It is very likely to face a ripple effect or interruption in the chain after supply disruption, which in turn affects the chain process and changes the supply and demand process. The ripple effect disrupts SC in both areas of process and structure in the manner of dominoes (Ivanov, 2018). If the supply chain managers do not address the issue of disruption risk and the knock-on effects as well as supply chain risks, do not estimate their probability, do not take preventive measures into consideration, or do not have the appropriate and prompt responses, they will move the chain away from its objectives, which are greater efficiency, accountability, and profitability. Several key performance measures, including revenue, sales, delivery time, service quality, and total profit, may be used to evaluate SC's deteriorating performance, which is triggered by severe interruptions. These risks are new obstacles for companies confronted with a domino effect owing to susceptibility, instability, and SC disruptions. Thus, this research seeks to survey supply chain disruption propagation. Regarding the prevalence of disruption factors in the world today, including the coronavirus outbreak, manufacturers and distribution centers are concerned that their suppliers will be disrupted and this disruption will propagate forward and downward throughout the chain and make it impossible to achieve goals, such as performance level, service level and delivery time, or leads to partial or complete SC disruption. Therefore, the goal of this study is to develop a criterion for measuring the ripple effect by simulating the ripple effect brought on by a supply chain disruption by combining a discrete-time Markov chain and a Bayesian network. This will allow us to determine how vulnerable the supply chain is to disruptions both before and after they occur and will aid managers in determining the best course of action to slow down the chain's recovery and disruption propagation, which will lower costs later on. The novelty of the present study is the quantitative estimation of the risk of a ripple effect by integrating the Markov chain with the Bayesian network, based on the lead time and lost sales for a three-tier supply chain. Our articulated Markov model is built for long-term disruptions; it shows that a disruption may remain in the supply chain for several periods of time. This research has presented a model that compares the results of a manufacturer disruption and a supplier disruption. As we show in the next section, the results of a review of the previous studies, the disruption affects the performance of the supply chain, and this has encouraged us to quantify the ripple effect by performance variables. Since the Covid-19-related disruption has led to the most damage to the delivery time and reduced sales in SCs, we selected the lead time and lost sale to model the ripple effect. We considered in the articulated Markov model, unlike other researches, the disruption in several consecutive periods in the supply chain. We also examined and compared the manufacturer disruption and supplier disruption besides the supplier disruption model. The model and the relationship, as presented in this research, can investigate the disruption at any point of the supply chain. This essay's remaining sections are organized as follows: In Section 2, there is a review of the literature on SC disruption. The approach and model presentation are explained in Section 3. Our model for estimating and analyzing simulation of the ripple effect caused by SC disruption is presented in Section 4. Finally, Section 5 discusses conclusions and discussions and the related suggestions.

2. Literature review

This section will follow the studies in two fields. First, we will discuss the researches on the ripple effect of the disruption and the management of the supply chain during the disruption. Then, we will examine many recent researches about the ripple effect of the disruption of Covid-19, because the disruption of Covid-19 has had a great impact on the supply chain.

2.1. Disruption and its management in the supply chain

Statistical analysis for supply chains (SCs) is a useful tool for recording their dynamics in terms of the complex systems that are prone to uncertainty (Rodger, 2014). Decisions on SC configuration are vital for any company. A production system's fundamental concern is SC risk and disruption. As a result of growth, complexity, and dependency of supply networks as well as the widespread use of demand-driven manufacturing processes, SCs have recently grown more susceptible to disruptions. Disruptions are defined as unusual conditions in the SC network that occur with low probability and high impact. The modern market is characterized by high levels of volatility and turbulence. Natural and man-made disruptions have a major impact on SC performance and impose huge costs to the chain in many cases. Therefore, the field of SC disruption management has attracted the attention of

many researchers, and many articles have been published in this regard. Disruption management has become more and more important in SC research as disruption risks have grown in frequency and severity (e.g., Hurricane Sally, Hurricane Zeta, Typhoon Goni, COVID-19 outbreak) (Hosseini & Ivanov, 2021). Risk identification, risk analysis, and risk mitigation make up the three components of the typical disruptive risk management plan for SCs (Zhang et al., 2018). New research on the ripple impact on strategy content has been inspired by the severity of the effects of the spread of SC disturbances and the unpredictable nature of disruptions (Ivanov, 2017; Sokolov et al., 2016). The downward propagation of the disruption's effects is seen by the ripple effect on SC content, which is related to structural dynamics. Examples of nonlinear SC content disruptions demonstrate that location disruptions are often unachievable owing to internal network links and outsourced operations. The substance and performance of a strategy may be adversely impacted by disruptions downstream, and this disruption propagation and lack of demand are the outcome of the ripple effect (Ivanov, 2018). There are several approaches to represent dependencies in SC management, such as the flow of commodities between a manufacturing and distribution hubs. Multiple interruptions and hazards may affect material flow (He et al., 2018; Ivanov et al., 2017; Pournader et al., 2020; Yoon et al., 2019). Controlling the ripple effect, i.e., the spread of a disturbance throughout a multi-tier supply chain, is among the primary problems in SC resilience management (Mishra et al., 2021). For instance, ripple effects were detected during the onset of the COVID-19 pandemic, resulting in SC disruption in Asia and potentially facility closures on other continents (Ivanov, 2020a). Due to the loss of experience and statistical data at the critical time when both tangible and intangible data should be used, the unprecedented disruptions that followed the COVID-19 pandemic made it difficult to understand the stimuli, potential consequences, and their impact on SC performance. Some of the distinctive features of BN, such as failure mode analysis and regression modeling (Wan et al., 2019), Monte Carlo simulation (Deleris & Erhun, 2005), and Markov chains (Hosseini et al., 2020), enable risk analysis and uncertainty management in complex SCs. Additionally, BNs are acknowledged as a good tool for assessing SC resilience in dynamics and capturing the dynamic character of disruptions and their spread, according to Hosseini and Ivanov (2017) and Liu et al. (2021). Llaguno et al. (2022) reviewed fifty recent articles related to the ripple effect. This article provides a conceptual framework of the latest articles on ripple effect and summarizes the factors contributing to disruption and stimulation of ripple effect and the methods of evaluating ripple effect and SC disruption propagation analysis presented by researchers. The researcher has discussed solutions to deal with the ripple effect. Resilience, agility and having safety reserves and alternative resources are some solutions to deal with the ripple effect, which were discussed in this article. It has a simulated analysis with the service level and profit criteria in a four-stage supply chain. An experimental study was undertaken by Duong et al. (2023) to look at how interruptions affect the functioning of the supply chain. The mechanism of ripple effects caused by interruptions has been discovered via a study on the concurrent impacts of risks on the efficiency of supply chains. They have created a theoretical framework using structural equation modeling with various hypotheses about the relationships between different types of risks and supply chain performance. They presented their research using information from a sizable survey funded by a Japanese government initiative to promote sustainable socio-economic development in Southeast Asian nations, which involved 207 enterprises. Research findings showed that human factors and drivers contribute to operational risks, while natural factors not only lead to operational risks but also supply risks. Bruuset et al. (2023) have proposed a dynamic optimization model for reorganizing the supply chain in the face of ripple effects caused by epidemic disruptions. This model assists managers in making optimal supplier selection within a planned horizon and improves vulnerabilities considering price and delivery time. Changes in circular flows within a supply chain network's reverberations were examined by Park et al. (2022). The use of circular flows in supply chain design has had a number of unintended consequences, which are discussed in this article. Circular flows are complicated and nonlinear in actual supply networks, but they are often hidden from supply chain management. In the supply chain network, some circular flows occur when a Tier 2 supplier serves as a Tier 3 (or higher) source. A circular network can also arise when a client and supplier are situated within the same network. When such systems are present, supply networks may have a ripple effect (or disruption propagation), in which disturbances affect how the supply chain runs. With the use of a real-world supply chain structure, they examined how circular flows create ripple effects and how resilient the supply chain is to disturbances. In complex supply networks, Chauhan et al. (2021) looked at the connection between interdependence patterns and ripple effects. They reviewed previous research on the emergence of interdependence and its potential drivers, while the relationship with supply network resilience remained largely unknown. In this study, they introduced a cascading model by juxtaposing the product-supplier-buyer structure and analyzing a geographical feature present in supply networks, providing novel insights. They simulated disruptions in interdependent and non-interconnected organizations within the global automotive supply network and found that interdependent organizations are substantially more immune to random disruptions but more vulnerable to cascading disruptions. However, because there are no other suppliers accessible, a responsive strategy whereby buyers look for alternatives does not help interdependent partnerships. Gholami-Zanjani et al. proposed a trustworthy location-inventory model for food supply networks that encounter ripple effects as a result of interruptions in 2021. In this article, they have developed a two-stage generalized combinatorial a mathematical model that incorporates the location-allocation and inventory-replenishment decision-making processes. Subsequently, the ripple effects of specific food-related disruptions are incorporated through acceptable scenarios. To deal with uncertainties in these contexts, three flexibility tactics are used: readiness, flexibility, and responsiveness. Based on the results of

the tests that were conducted, the results indicate how different models react to explicit ripple effects. Examining SC network resiliency in the existence of a ripple impact. The objective of this research was to examine the overall resilience of the supply chain network resilience (SCNR) in the face of a cascading impact or risk dissemination, i.e., disruptions in the supply chain networks (SCN) of many organisations might propagate to nearby enterprises. Eventually, it expanded to the SCN of other firms. For assessing SCNR, a quantitative method based on three different network performance measures and three resilience features has been developed. Dong et al. (2020) surveyed the ripple effect on environmental adjustment in China. Environmental adjustment and the development of green technology are important tools to address the negative effects of environmental pollution. Despite widespread concerns about the effect of environmental regulations on the development of green technology, the literature on the relationship among them focuses mainly on local areas of the same area and few convincing kinds of research. According to the dynamic spatial durbin panel model, this article investigates the ripple effect of environmental regulation using provincial-level data in China, and further investigates the mechanism of ripple effect formation in environmental adjustment. Using factor-based simulations, Lohmer et al. (2020) studied resilience techniques and the ripple effect in blockchain-coordinated SCs. Resilience allows SCs to lessen disruptions and recover more quickly. Using a Markov chain and dynamic Bayesian network technology, Hosseini et al. (2020) provided a methodology for calculating the ripple effects of supply interruptions in terms of service level and projected utility. The ripple effect in the two-stage supply chain was discovered with the aid of the integration of a discrete-time Markov chain (DTMC) and a dynamic Bayesian network (DBN). DTMC was also used to predict supply recovery and vulnerability. Combining the suggested DTMC model with a DBN model, researchers were able to simulate how supply interruptions in SCs propagate. These results imply that the model may discover hidden high-risk routes in SCs, assess the effect of disruption and its repetition, and prioritise preventative and recovery actions.

2.2. Covid-19-related disruption and its impact on supply chain

Covid-19 outbreak inflicted a major supply chain ripple effect and reduced sales. This pandemic had a negative shock on the supply and demand and has spread to all sectors of the economy by affecting SCs. Through the simulation of dynamic systems, Ghadge et al. (2022) have investigated the adverse impacts of long-term and concurrent interruptions brought on by COVID-19. The major aim of the current study was to discover the value of dynamic systems approach in identifying and visualizing ripple effects along with analyzing dynamic behaviors of production and distribution at different levels of the supply chain. They have investigated four disruption scenarios arising from demand, procurement, supply, and combined (simultaneous) risks. The findings demonstrated that the spread of disruptions and their effects rely on the types of risks and combinations, with distributors and manufacturers being more susceptible to many and protracted disruptions as a result of broader and more delicate risk points. In reaction to pandemic disruptions, Bruuset et al. (2022) developed a model of the impact of ripple propagation and employee productivity in the global supply chain. They have demonstrated how the geographical spread of a pandemic amplifies ripple effects by reducing labor participation in production, weakening the capabilities of companies and the entire global supply chain to meet customer demands. The spatiotemporal dynamics of COVID-19 spread in supply networks and its methodologies aid in visualizing and assessing ripple effects by simulating the movement of materials and goods in a typical global supply chain using an epidemiological model. To predict the influence on the workforce at each node, the model conducts future-focused studies in "what-if" scenarios. The results of this study contribute to increasing the supply network's resilience to cascading effects and reducing the impact and spread of a pandemic in a specific area. In 2022, Sindhwani, Jayaram, and Sedikuti conducted a study on the possibility of reducing knock-on effects in India's pharmaceutical delivery network in the event of interruptions like the COVID-19 pandemic. Bayesian networks, mathematical optimization, and discrete event simulation techniques were used in multilayer research (network, process, and control levels) to assess the mitigation capability. This investigation showed a link between the supply chain's upstream inventory network's design elements and mitigation capabilities. Through random optimization and Lagrange relaxation, they identified ideal options for regional distribution centers at the lower level and integrated these lower-level locations with other entities in the supply chain to construct an optimization and simulation model of the network for overall system performance analysis. The usefulness of the proposed method was demonstrated by a case analysis including the distributing of N95 masks at Indian Janaushadhi stores during the COVID-19 pandemic. According to the findings, supply chain reconfiguration can raise service levels by up to 95.7% while lowering order volume by 10.7%. The flexibility offered by regional distribution hubs and backup sourcing improves workplace health and safety. Jingzhe et al. (2022) presented a disruption recovery strategy in the supply chain considering product switching during the COVID-19 pandemic. The recent global outbreak of the coronavirus has led to widespread disruptions in the supply chain, posing challenges for manufacturers to recover their supply chains in the short term. This article offers a disruption recovery method that was inspired by the primary product's modification. A mixed-integer linear programming (MILP) model is designed to combine emergency procurement on the supply side, product adjustments by the manufacturer, as well as price compensation after ordering on the demand side, in order to maximise the overall profit from product changes. The ILOG CPLEX-based heuristic algorithm is used in this model. Empirical findings show that the suggested disruption recovery technique can successfully reduce the manufacturer's loss of profit caused by delivery delays and order cancellations. Ivanov (2020a) was the first to

look at the pandemic's impact on SCs. Using any Logistix software, he created a discrete-event simulation (DES) model to predict the effects of a pandemic on SC, including service quality, lead time, and payback rate. The closure and opening periods of the plant at various levels were shown to be the most important indicators of the impact of the COVID-19 epidemic on SC performance, not the length of the upstream interruption or the pace of COVID-19 spread, according to the author. Ivanov also looked at how different retrieval strategies affected the pandemic's prevalence. Ivanov and Dolgui (2020) looked at the relevance of interconnected supply networks' (ISNs') capacity to function in the COVID-19 era. They discovered that ISNs lessen SC disruptions by taking survival and viability into consideration and used a dynamic game theory technique to show the viability formation for ISNs. A simulation model was developed by Singh et al. (2021) to monitor SC response during COVID-19. Their simulation model's findings indicate that combining warehouses may significantly increase capacity to fulfill demand. Ivanov (2020b) examined the development of practical SCs for managing COVID-19-related circumstances. Using dynamic system theory, he showed how to combine robustness, agility, and sustainability to create VSCs. The three primary components of the VSC model are the SC ecosystems, different SC network topologies, and viability capabilities, which are given below. Due to the switching of COVID-19 products, Chen et al. (2021) presented a supply chain disruption recovery method. The recent worldwide epidemic of COVID-19 has caused significant disruption of SCs, making it impossible for producers to recoup their SCs in the near future. In this work, the SC disruption recovery approach is described in an effort to alter the primary product type. To optimise the overall profit from product modifications, a MILP model was developed by integrating emergency purchases on the supply side, product adjustments by the manufacturer, and post-order price compensation on the demand side. This model employs an innovative ILOG CPLEX-based algorithm. The findings of an experiment indicate that the suggested disruption recovery technique may successfully decrease the manufacturer's profit loss caused by delivery delays and order cancellations. To address the COVID-19 pandemic's ripple impact on SCs, Ivanov and Dolgui (2021b) developed the OR approach. According to the author, COVID-19 causes SCs to become unexpectedly and unpredictably fragile and is a significant factor in SC stress and subsequent shocks owing to disruption propagation (such as the ripple effect). Li et al. (2021) studied the ripple effect on SCN with regard to both upward and downward disruption propagation, network health, and vulnerability in their study. A small disturbance may spread across the network and ultimately impact the whole SCN. This phenomenon is a widespread phenomenon known as the ripple effect that has attracted much attention in recent years. In addition, forward and backward prorogation interruptions are a key stressor for SCNs during the COVID-19 pandemic, since they are triggered by consecutive supply and demand disruptions. A workable BN model with three levels of disruption triggers, risk events, and repercussions was established in the first study by Hosseini and Ivanov (2021). According to this paradigm, the occurrence of risk events defines the outcomes, whereas the occurrence of disruption triggers determines the occurrence of risk events. Conditional probability is used to describe the causal connections between these three levels. This model illustrates the interdependencies between risk occurrences. The suggested method also makes it possible to quantify how SC disruption triggers affect financial performance (Such as missed sales) and operational continuity. It also offers insight into the likelihood of mitigating disruption triggers to reduce the likelihood and effect of SC interruptions. After reviewing the related literature and understanding that Covid-19 disruption in SCN has a significant effect on the customer lead time and the number of sales in the downstream chain, this research will provide a criterion to quantify the effect of this disruption in terms of lead time and lost sales in a three-stage SC.

3. Methodology

3.1. Description of model expressions

π_0, π_1 and π_2 : It represents the probability of an existence of a supplier in state 0, 1 and 2.

λ_1 : the transfer rate of supply chain members from an operational state to a disrupted state

λ_2 : the transfer rate of supply chain members from an operational state to a semi-operational state

λ_3 : the transfer rate of supply chain members from a semi-operational state to a disrupted state

μ_1 : the transfer rate of supply chain members from a disrupted state to an operational state

μ_2 : the transfer rate of supply chain members from a disrupted state to a semi-disrupted state

μ_3 : the transfer rate of supply chain members from a semi-operational state to an operational state

α : the transfer rate of supply chain members from an operational state to an operational state

γ : the transfer rate of supply chain members from a semi-operational state to a semi-operational state

β : the transfer rate of supply chain members from a disturbed state to a disturbed state

SC: Supply chain

DTMC: Markov Discrete-Time Chain

CPT: Conditional Probability Table

DBN: Dynamic Bayesian Network

Lt: lead time

Ls: lost sales

Els: Estimate lost sales

TELS: Total Estimate Lost sales

3.2. Proposed Markov chain model

In order to replicate a supply chain behaviour in the case of a long-term (given that the disruption, like the disruption of Covid-19, may remain in the supply chain for several periods) interruption, a Markov chain model is presented in this section. Think about member of the supply chain whose actions may be categorised into three categories. For example, the supplier can withstand disruption-related shocks in State 0, also known as the operational state, without suffering capacity loss. It loses half of its capability in Condition 1, the semi-operational or semi-disrupted state. Due to the intensity and scope of the interruption, it loses all of its capability in Mode 2. For the sake of simplicity, we only take into account one kind of semi-disrupted mode, which denotes a situation where a provider loses fifty percent of its capacity in the case of a disruption. The suggested Markov chain model (Figure 1) has three unique states (0, 1) and (2) that are used to account for a supplier's capacity losses after an interruption. Imagine that a provider is operating normally before an interruption. In the event of an interruption, the providers can handle the shock without losing capacity. A self-loop is used to simulate this scenario in State0, the absorber or operating state. On the other side, if there is an interruption, the provider can lose 50% of its capacity. The output arc from State 0 to State 1 takes this into account. Otherwise, in the case of a high-severity mishap, the provider loses all of its operating capability. Getting to this situation requires going from State 0 to State 2. Now, suppose a supplier is semi-disrupted and is in State 1 at time t . This supplier can return its lost capacity by moving backwards from State 1 at time t to State 0 at time $t + 1$, or go to a disrupted state (State 2), or it may not be able to recover itself and stay in the same semi-disrupted State at time $t + 1$. Finally, consider a case where the supplier is disrupted at time t and can recover all its lost capacity at time $t + 1$, which is achieved by the input arrow from State 2 to State 0. It can recover 50% of the lost capacity at time $t + 1$ and the rest at time $t + 2$, or it can stay in the disrupted state at time $t + 1$. This is indicated by three output arrows from State 2 to State 1, State 1 to State 0, and State 2 to State 2. It is noteworthy that π_0 , π_1 and π_2 indicate the possibility of a supplier in the State 0, 1 and 2. The transition rate from one state to another is denoted by α , λ_1 , λ_2 , μ_1 , μ_2 , λ_3 , and μ_3 and γ and β (Figure 1). Equations (1–4) display the equations that were written for this model. The likelihood that a provider is in States 0, 1, and 2 can be calculated by solving the ensuing equations. Knowing the likelihood of each stage will help the supplier better understand his or her susceptibility and develop a strategy to lessen the interruption.

$$(\alpha_1 + \mu_1 + \mu_3)\pi_0 = \lambda_1\pi_2 + \lambda_2\pi_1 \quad (1)$$

$$(\lambda_2 + \mu_2 + \gamma)\pi_1 = \mu_3\pi_0 + \lambda_3\pi_2 \quad (2)$$

$$(\lambda_1 + \lambda_3 + \beta)\pi_2 = \mu_1\pi_0 + \mu_2\pi_1 \quad (3)$$

$$\pi_0 + \pi_1 + \pi_2 = 1 \quad (4)$$

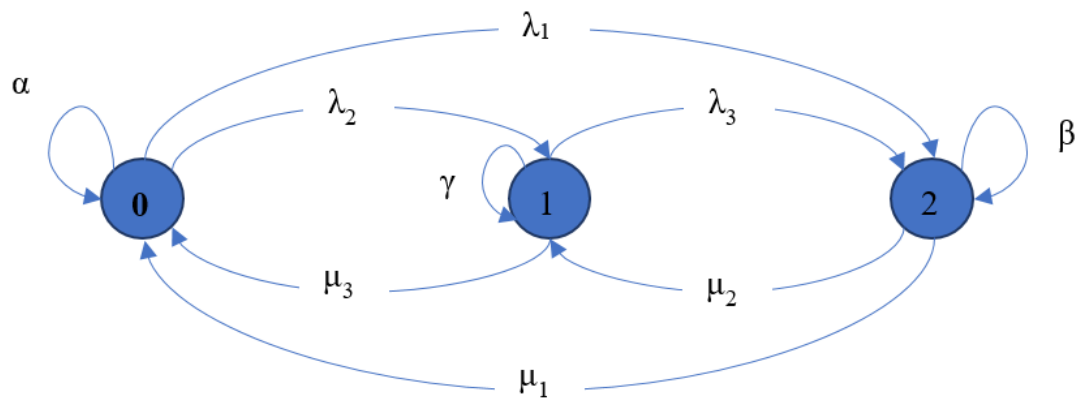


Figure 1. Model of discrete-time Markov chains for interruption of supplier capacity

3.3. Equivalent dynamic Bayesian network model

3.3.1. Bayesian network theory

Bayesian networks (BNs) are recognized as an effective tool for determining risks, managing uncertainty, and making decisions. Combining historical data and professional expertise, BNs can quantify risk via the use of graphical representations of causes and consequences. Based on Bayes' theorem, BN is a non-rotating graphical model with a probabilistic orientation. When creating a probabilistic causal model, such as a Bayesian network (BN), it is customary to incorporate specialised knowledge about decision-analysis-relevant aspects when historical data are unavailable or difficult to get (Constantinou et al., 2016; Hosseini & Barker, 2016a; Hosseini & Barker, 2016b; Hosseini et al., 2016a; Hosseini et al., 2016b; Qazi et al., 2018; Song et al., 2013). BNs were often used to solve risk management issues. Mathematically, BNs may be thought of as directed acyclic networks with a set of nodes (variables), designated by $V = X_1, X_2, \dots, X_n$, and a collection of arcs (edges) whose structure controls the interaction between the nodes. The output arc from X_i to X_j shows that the value of the variable j depends on the value of X_i ; hence, these nodes are referred to as the parent and child nodes, respectively. Three main sorts of nodes can exist in BNs: Nodes are categorized as root nodes, leaf nodes, or intermediate nodes based on whether they have a parent node and a child node, according to Hosseini and Barker (2016a). The chain law enables the joint probability of all variables (nodes) to be calculated by multiplying the conditional probability of each node:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | X_1, X_2, \dots, X_{i-1}) \quad (5)$$

Think of a BN model with four variables, for example. Figure 2 shows that X_1 is the root node, X_2 and X_3 are intermediate nodes, and X_4 is a leaf node. In BNs, conditional probability is employed to establish a causal connection between the variables. The joint probability distribution (JPD) of BN models may be used to visualize the BN structure and the inter-variable dependency. The previous odds, $P(x_1)$, as well as the contingent likelihoods, $P(x_2 | x_1)$, $P(x_3 | x_2)$, and $P(x_4 | x_2, x_3)$, must be specified in the aforementioned case. According to Figure 2, the JPD for the BN model has been calculated:

$$P(X_1, X_2, X_3, X_4) = P(x_1)P(x_2|x_1)P(x_3|x_2)P(x_4|x_2, x_3) \quad (6)$$

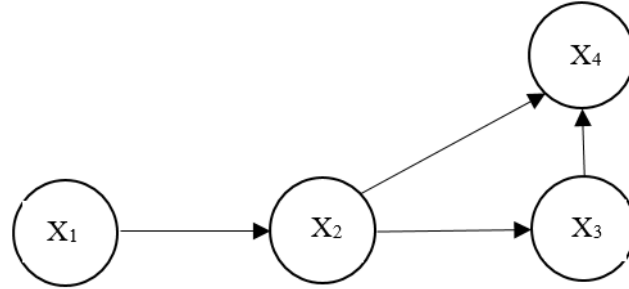


Figure 2. A four-node BN (Hosseini et al. 2020).

Each node in BNs has a conditional probability table (CPT) attached to it that calculates the likelihood of each node occurring given the values of the other nodes. (Hosseini & Barker, 2016a). It is noteworthy that CPT can express the conditional probability between two nodes.

JPD can be applied to compute the probability of individual nodes in a BN. Suppose we are interested in calculating X_2 , then $P(X_2)$ can be written as follows:

$$P(x_2) = \sum_{x_1, x_3, x_4} P(x_1)P(x_2|x_1)P(x_3|x_2)P(x_4|x_2, x_3) \quad (7)$$

Applying the marginalization approach, the aforementioned equation may be reformulated as illustrated in Equation 8 (Hosseini et al., 2020).

$$P(x_2) = \left(\sum_{x_1} P(x_1) \left(\sum_{x_3} P(x_3|x_2) \left(\sum_{x_4} P(x_4|x_2, x_3) \right) \right) \right) \quad (8)$$

To explain Equation (8) and better understand BN, a simple Bayesian network with one distributor and two manufacturers were presented in Figure 3

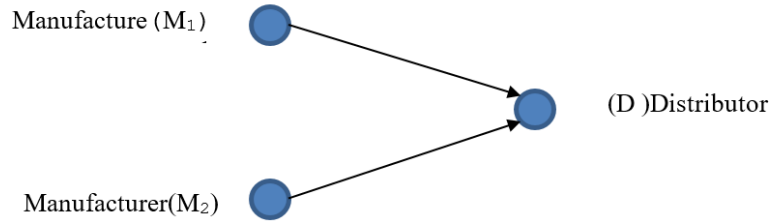


Figure 3. Simple BN with two manufacturers and one distributor.

The procedure for calculating the risk of distributor interruption based on the conditional probability table specified in equation (9). Table 1 assumes two operational and disturbed states for the purpose of simplicity, which may be extended to three states in Equation 9. In addition, equations were developed to determine the operational and semi-operational probability state of the distributor omitted. The relationship to determine the status of manufacturers in the three-stage supply chain is provided based on CPT between manufacturers and suppliers.

Table 1. Conditional probability table (CPT) of the distributor disruption.

M1	Operational		Disrupted	
M2	Operational	disrupted	Operational	disrupted
D	Operational	Operational	Operational	Operational
	Disrupted	disrupted	disrupted	disrupted

$$\begin{aligned}
 P(D \text{ disrupted}) &= \sum_{s_1, s_2} P(D \text{ disrupted} | m_1, m_2) \\
 &= P(D \text{ disrupted} | m_1 = \text{disrupted}, m_2 = \text{disrupted}) \times P(m_1 = \text{disrupted}) \times P(m_2 = \text{disrupted}) \\
 &+ P(D \text{ disrupted} | m_1 = \text{operational}, m_2 = \text{disrupted}) \times P(m_1 = \text{operational}) \times P(m_2 = \text{disrupted}) \\
 &+ P(D \text{ disrupted} | m_1 = \text{disrupted}, m_2 = \text{operational}) \times P(m_1 = \text{disrupted}) \times P(m_2 = \text{operational}) \\
 &+ P(D \text{ disrupted} | m_1 = \text{operational}, m_2 = \text{operational}) \times P(m_1 = \text{operational}) \times P(m_2 = \text{operational})
 \end{aligned} \tag{9}$$

3.3.2. Dynamic Bayesian network

A subset of a static Bayesian network (BN), a dynamic Bayesian network (DBN), replicates the network across the required number of time steps to account for the time dimension. A stochastic process in a dynamic setting can be described by a DBN. Cai et al. (2016), Barua et al. (2018), Marcot and Penman (2018), Rebello, Yu, and Ma (2018), Hosseini and Sarder (2019), Hosseini et al. (2019), and Ivanov et al. (2019) all provide various DBN applications for risk assessment. Since the ripple impact of a supply disruption is unpredictable and dynamic, DBN is an appropriate way of documenting it. The following three key hypotheses are taken into account in order to streamline the ripple effect modeling procedure:

- Since the conditional probability table (CPT) with regard to the BN topology does not change over time, the system is said to be time constant.
- Since this is a Markovian process, the probability distribution of the state at time $t + 1$ depends only on the circumstances at time t and not on the sequence of events that came before it.
- Supplier transition probability matrix and conditional probability tables of the manufacturer and distributor in different periods are assumed to be constant.

These presumptions lead to the definition of DBN as the growth of a static BN with various periods. Figure 4 displays an easy DBN. This shows how the variables at time t and time $t + 1$ are related. The supplier probability distribution at time $t + 1$ depends on its probabilistic distribution at time t , as depicted in Figure 4. In a dynamic setting, JPD of DBN can be depicted as follows:

$$P(X_{1,t}, X_{2,t}, \dots, X_{n,t}) = \prod_{t=1}^T \prod_{i=1}^N P(X_{i,t} | X_{1,t}, X_{2,t}, \dots, X_{i-1,t}) \tag{10}$$

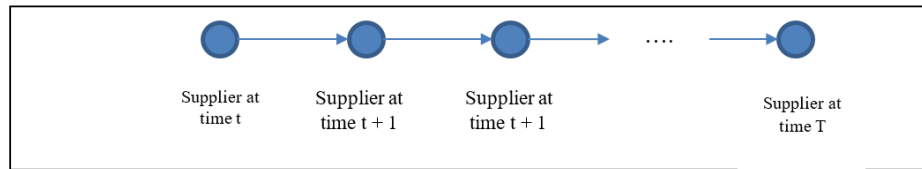


Figure 4. Dynamic Bayesian network of suppliers with time T periods (Hosseini et al., 2020)

3.3.3. Transition probability matrices when individual transitions known

A significant challenge in the DBN structure is determining the transition probability by changing the status of variables throughout time. When describing the dynamics of changes in credit quality, transition matrices are often employed in the credit rating literature. Due to the fact that they are based on the Markov transition probability model, these matrices offer a clear technique for describing the development of credit ratings. Starting with a set of discrete credit modes, which can be used to classify all data, the Markov transition probability model may be used. Assume that there are R discrete categories in which all observations may be arranged. A transition matrix, $P = [p_{ij}]$, can be defined as a probability matrix that shows the likelihood that a state will change or transition to any of the other R-1 categories during a specific time frame. The chance that states i in period t-1 switches to state j in period t is displayed for each member of the p_{ij} matrix (Jones, 2005):

$$\begin{bmatrix} p_{11} & p_{12} \dots & p_{1R} \\ p_{21} & p_{22} \dots & p_{2R} \\ \vdots & \vdots & \vdots \\ p_{R1} & p_{R2} \dots & p_{RR} \end{bmatrix} \quad (11)$$

If n_{ij} shows the number of people who were in state i at period t-1 and are in state j at period t, we can estimate the probability of a person being in state j at t applying the following formula. Since they were in state i at t-1, this probability is denoted by p_{ij} :

$$p_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \quad (12)$$

Regarding the supplier, manufacturer and distributor status is accessible in the past few periods in the studied chain, Equations (11) and (12) are applied in the DBN model presented in this study to provide the transition matrix.

3.4. Ripple effect modeling

When the disruption effect cannot be stopped at the upstream SC and spreads downstream, it has an adverse influence on the downstream SC's performance in terms of cost, service level, and lead time (Hosseini et al., 2020). Delivery time or lead time is subdivided into operational, semi-disrupted, and disrupted states of SC components, namely suppliers, manufacturers, and the distribution center, which is influenced by the status of suppliers. The lead time (L_t) of a supplier may vary based on whether the provider is operating, semi-interrupted, or disrupted. Consequently, variable L_t is dependent on the supply state from BN's perspective. It is thought that variable L_t consists of three modes: low, medium, and high, which indicates that, depending on the status of the distributor, the items are delivered on time or with a significant delay. We have defined the likelihood of being in the L_t condition (Table 2). For each SC, the delivery time or lead time level may be set, as illustrated in Table 2 for the linguistic variable of lead time.

Table 2. The linguistic variable of lead-time (L_t) level.

Linguistic symbol of lead time level	Delivery time or lead time (L_t)
Low	Delivery of goods in a period that is less than or equal to the desired time from the customer perspective
Medium	Delivery of goods in a period that is longer than the desired time from the customer's perspective and is shorter than the time that is unacceptable for the customer
High	Delivery of goods at a time when it is unacceptable for the customer (exceeding the customer's expectations)

Based on each lead time state (low, medium, high), the amount of sales changes. For each level of delivery time, lost sales can be defined, which are represented by low Ls, medium Ls and high Ls. The amount of lost sales is also high in the case of high lead time, and vice versa, the lost sales are low for the low lead time. Hence, we will use lead time and decision tree to model the ripple effect. According to the above assumptions, we draw the desired decision tree for the supplier in Figure 5. We define a criterion (Equation 13) to predict the lost sales for low lead-time probability (Figure 5).

$$ELs^{Low} = [P(Operational) \times P(Low_{Lt}|Operational) \times Low_{Ls} + [P(Semi - disrupted) \times P(Low_{Lt}|Semi - disrupted) \times Low_{Ls}]] + [P(disrupted) \times P(Low_{Lt}|disrupted) \times Low_{Ls}] \quad (13)$$

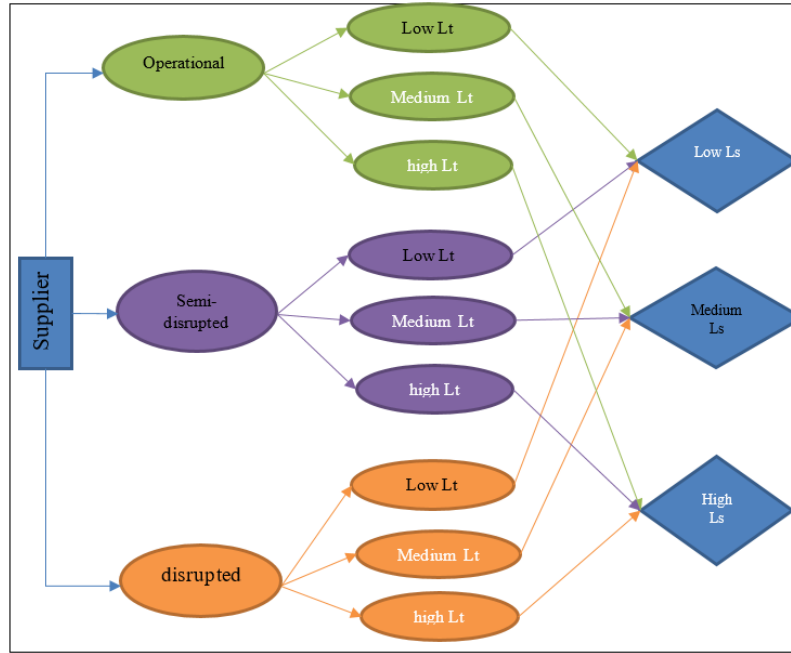


Figure 5. The decision tree of supplier status, lead time, and lost sales states.

Equation 13 can be generalized to the medium- and high-lost sales for the supplier and finally the sum of the total lost sales to the supplier can be predicted as indicated in Equation 14 (see Figure 6).

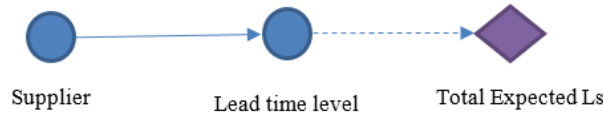


Figure 6. Total estimate lost sales (TELS) of suppliers.

$$TELS_{supplier} = ELs_{slow} + ELs_{medium} + ELs_{high} \quad (14)$$

A similar total estimate lost sales can be computed for the manufacturer and distributor, whose relationships are given in Equations 15 and 16.

$$TELS_{manufacturer} = ELs_{slow} + ELs_{medium} + ELs_{high} \quad (15)$$

$$TELS_{distributor} = ELs_{slow} + ELs_{medium} + ELs_{high} \quad (16)$$

At last, the sum of the total SC sales is obtained in a time horizon according to Equation 17.

$$TELS_{supply\ chain\ T} = TELS_{supplier1\ T} + TELS_{supplier2\ T} + TELS_{manufacturer\ T} + TELS_{distributor} \quad (17)$$

To demonstrate the ripple effect caused by a supply disruption on a three-stage SC over a time horizon, we can only obtain and compare the total lost sales of the distributor in different time periods. It is also possible to calculate and compare the total lost sales of the supply chain (total lost sales of suppliers, manufacturers, and distributors) in each period in order to comprehend the time-horizon-spanning ripple effect of a disruption. To develop the general criterion of the ripple effect model and obtain the lost sales of each component of the chain as well as the entire supply chain, a three-stage chain with m suppliers, n manufacturers and f distributors with 3 operational and semi-disrupted and disrupted states denoted by k , as well as the three levels of delivery or lead time denoted by l , are considered along the time horizon T . According to the stated concepts and assumptions, TELS for all suppliers can be calculated using Equation (18).

$$TELS_{Suppliers} = \sum_{t=1}^T \sum_{i=1}^m \sum_{k=1}^3 \sum_{l=1}^3 P_{ikt} \times P_{iklt} \times Ls_{ikt} \quad (18)$$

The TELs of all manufacturers along the time horizons T can be obtained by Equation (19):

$$TELS_{Manufacturers} = \sum_{t=1}^T \sum_{j=1}^n \sum_{k=1}^3 \sum_{l=1}^3 p_{jkt} \times p_{jkl} \times LS_{jkl} \quad (19)$$

The TELs of all distributors along the time horizons T can be obtained by Equation 20:

$$TELS_{Distributors} = \sum_{t=1}^T \sum_{r=1}^f \sum_{k=1}^3 \sum_{l=1}^3 p_{rkt} \times p_{rkl} \times LS_{rkl} \quad (20)$$

Finally, TELs of a time horizon is obtained by Equation (21).

$$TELS_{Supply\ chain} = \sum_{t=1}^T \sum_{i=1}^m \sum_{k=1}^3 \sum_{l=1}^3 p_{ikt} \times p_{ikl} \times LS_{ikl} + \sum_{t=1}^T \sum_{j=1}^n \sum_{k=1}^3 \sum_{l=1}^3 p_{jkt} \times p_{jkl} \times LS_{jkl} \\ + \sum_{t=1}^T \sum_{r=1}^f \sum_{k=1}^3 \sum_{l=1}^3 p_{rkt} \times p_{rkl} \times LS_{rkl} \quad (21)$$

In SC, the ripple effect caused by a supply interruption may be calculated using Equation 21. In the next part, a case study will be used to illustrate the aforementioned model and equations and demonstrate the ripple impact on SCs.

4. Case study and discussion

We examined a supply chain as a case study in order to investigate and analyze our model. One supplier of this supply chain is in China. The supplier in China has been disrupted and interrupted at the beginning of the epidemic of Covid-19 and before its spread in the place of establishment of this chain. Because we considered the last major disruption of the last few years in our research, we chose this chain; it has three suppliers, two manufacturers and one distributor. The supply chain of the voltage converter, which consists of three layers (Figure 7) of supplier, manufacturer, and distributor, is provided with the model, analysed as a case study of the ripple impact produced by Covid-19-related interruption, and the findings are given. The voltage converter is comprised of several components. Only the two main components of the electrical kit and the high voltage, which play a significant influence in the manufacturing and production time of this device and are outsourced by the manufacturers, have been analysed in this research. In this supply chain, there is one distributor, two manufacturers, and three suppliers. Between two joint producers there is one supplier. If we consider the time of production and delivery of supplied items by suppliers to the manufacturer as t, goods are produced by manufacturers at t + 1 and goods are delivered to the customer at t + 3.

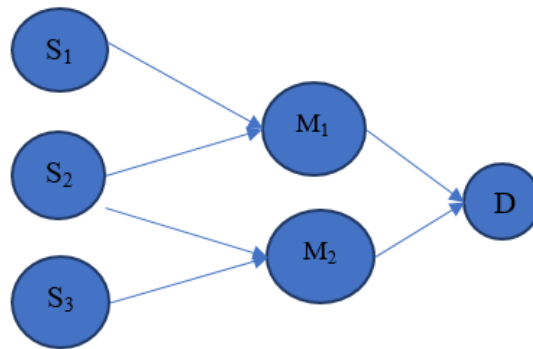


Figure 7. Three-stage supply chain of voltage converter production.

4.1. Model analysis with supply chain data before disruption

After receiving data from sixty time periods related to suppliers in this supply chain (before Covid-19 virus disruption in China), the transition rate of suppliers according to the Markov model is presented below (see Figure 1):

Supplier 1 in these sixty periods is operational, semi-disrupted and fully-disrupted states in 47, 9 and 4 periods, respectively and its transition rate is $\alpha = 40$, $\lambda_2 = 6$, $\lambda_1 = 1$, $\mu_3 = 6$, $\gamma = 1$, $\lambda_3 = 2$, $\mu_1 = 1$, $\mu_2 = 2$, $\beta = 1$. In these sixty

periods, supplier 2 was also at operational, semi-disrupted and fully-disrupted states at 55, 4 and 1 period, respectively and its transition rate was $\alpha = 53, \lambda_2 = 2, \lambda_1 = 0, \mu_3 = 2, \gamma = 1, \lambda_3 = 1, \mu_1 = 0, \mu_2 = 1, \beta = 0$. Supplier 3 was at operational, semi-disrupted and fully-disrupted states at 52, 7 and 1 period, respectively and its transition rate was $\alpha = 47, \lambda_2 = 2, \lambda_1 = 1, \mu_3 = 5, \gamma = 2, \lambda_3 = 0, \mu_1 = 0, \mu_2 = 1, \beta = 0$. According to Equation 12, the transition probability matrix for suppliers is provided (Table 3).

Table 3. Conditional probability table (CPT) transition for suppliers in three states.

		t+Δt								
		Supplier 1			Supplier 2			Supplier 3		
t		Operational	Semi-disrupted	disrupted	Operational	Semi-disrupted	disrupted	Operational	Semi-disrupted	disrupted
Operational		0.85	0.13	0.02	0.96	0.04	0.00	0.9	0.08	0.02
Semi-disrupted		0.67	0.11	0.22	0.50	0.25	0.25	0.71	0.29	0.00
Disrupted		0.25	0.50	0.25	0.00	1	0.00	0.00	1	0.00

As consulted with statisticians, the probability of operational, semi-disrupted and disrupted states for suppliers before Covid-19 disease was obtained at 90%, 7% and 3% for Supplier 1, 96%, 3% and 1% for Supplier 2, 95, 3% and 2% for Supplier 3, respectively. The status of conditional probabilities of manufacturers and distributors in the chain is presented in Tables 4 to 6.

Table 4. Conditional probability table (CPT) of the disruption for manufacturer 1.

S1	Operational			Semi-disrupted			Disrupted		
S2	Operational	Semi-disrupted	disrupted	Operational	Semi-disrupted	disrupted	Operational	Semi-disrupted	disrupted
Operational	0.91	0.79	0.15	0.6	0.16	0.11	0.09	0.07	0.01
Semi-disrupted	0.08	0.16	0.33	0.34	0.69	0.37	0.15	0.12	0.05
disrupted	0.01	0.05	0.52	0.06	0.15	0.52	0.76	0.81	0.94

Table 5. Conditional probability table (CPT) of disruption for manufacturer 2.

S3	Operational			Semi-disrupted			Fully-disrupted		
S2	Operational	Semi-disrupted	disrupted	Operational	Semi-disrupted	disrupted	Operational	Semi-disrupted	disrupted
Operational	0.94	0.81	0.19	0.65	0.2	0.13	0.1	0.09	0.01
Semi-disrupted	0.05	0.17	0.36	0.31	0.77	0.37	0.15	0.13	0.06
disrupted	0.01	0.02	0.45	0.04	0.03	0.5	0.75	0.78	0.93

Table 6. Conditional probability table (CPT) of the distributor disruption.

M1	Operational			Semi-disrupted			Fully-disrupted		
M2	Operational	Semi-disrupted	disrupted	Operational	Semi-disrupted	disrupted	Operational	Semi-disrupted	disrupted
Operational	0.92	0.62	0.45	0.65	0.19	0.1	0.55	0.12	0.01
Semi-disrupted	0.05	0.3	0.45	0.3	0.77	0.22	0.36	0.25	0.06
disrupted	0.03	0.08	0.1	0.05	0.04	0.68	0.09	0.63	0.93

A 60-period analysis of the sales data in this SC reveals that the volume of sales is closely proportional to the lead time. In this supply chain, the ideal customer lead time is one month, and the maximum number of missed sales is 300 units. One month and one day to two months is also considered to be a medium lead time, with a maximum of 2,000 units lost in sales; more than two months was referred to as the unsatisfactory protracted lead time, with a maximum of 3,600 units lost in sales. The ripple effect in terms of supplier disruption on the distributor in the

studied supply chain based on the DBN model which is presented in Figure 8 and the decision tree (Figure 9) is quantified by the lead time for delivery of goods and lost sales. We defined in the method section the equation 21 to quantify the ripple effect and evaluate the lost sales of the entire supply chain. We will show and analyze in this section only the distributor's lost sales in Figure 8 for easier understanding and ignore the lost sales of the entire supply chain.

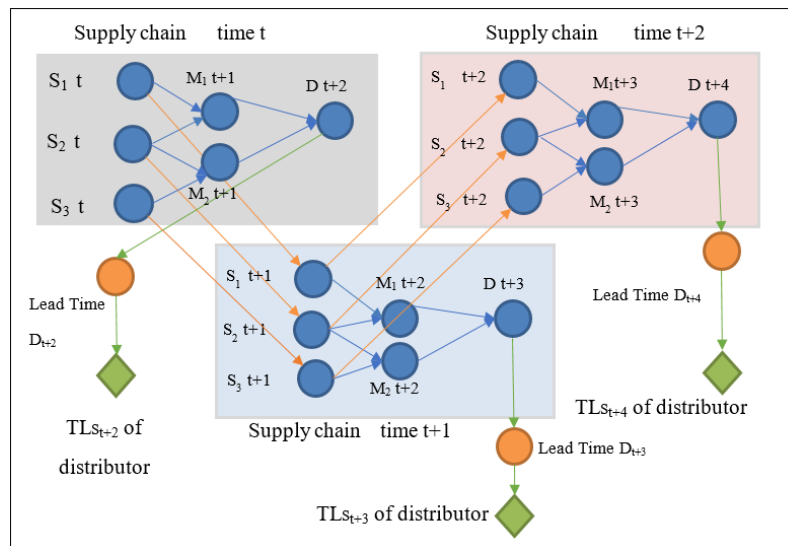


Figure 8. DBN model of a three-stage supply chain based on the lead time and lost sales for the distributor (model for evaluating the ripple effect).

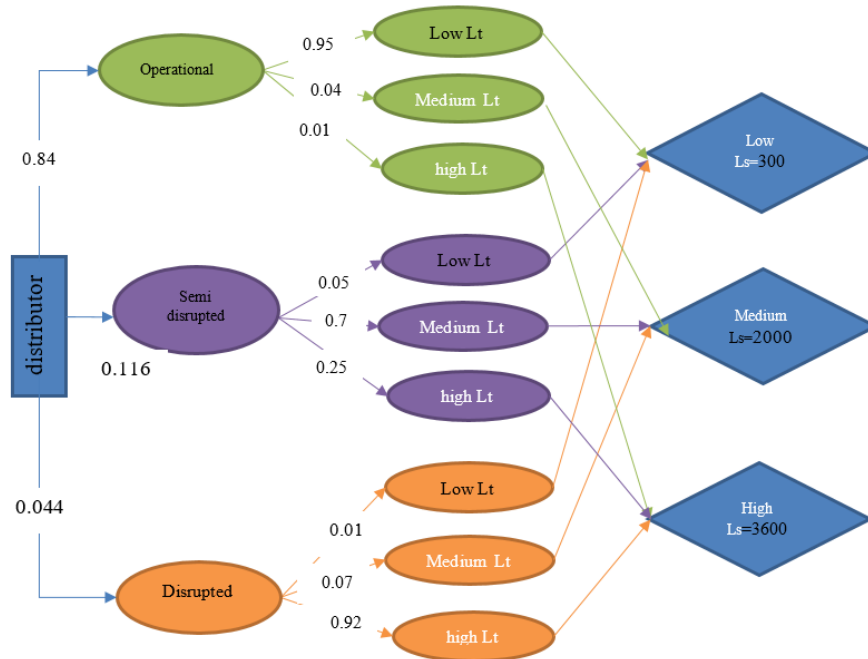


Figure 9. Distributor decision tree including the lead time and lost sales states.

The lost sales for the distributor at $t + 2$, according to Equation 22, is equal to 757 devices. To obtain the lost sales at $t + 3$ and $t + 4$, the same process was done and its lost sales are 797 and 820 devices, respectively. The sum of the total lost sales for suppliers and manufacturers before the current pandemic was predicted by 2374 devices (Figure 10).

$$EL_{slow} = (0.84 * 0.95 * 300) + (0.116 * 0.05 * 300) + (0.044 * 0.01 * 300) = 280.119 \quad (22)$$

$$EL_{Smed} = (0.84 * 0.04 * 2000) + (0.116 * 0.7 * 2000) + (0.044 * 0.07 * 2000) = 236.195$$

$$EL_{high} = (0.84 * 0.01 * 3600) + (0.116 * 0.25 * 3600) + (0.044 * 0.92 * 3600) = 241.227$$

$$TLS_{(t+1)} = 280 + 236 + 241 = 757$$

4.2. Ripple effect predict after Covid-19-related disruption

After Covid-19 pandemic in China, Supplier 1 was disrupted and its SC changed during periods $t + 1$ and $t + 2$, instead of proceeding based on previous prediction or normal routine (Figure 11). According to the figure, the supplier is disrupted at $t + 1$ and $t + 2$, which could not deliver the primary parts required by the manufacturer 1 in time, and the operational status of the manufacturer 1 decreased from 81.9% at $t + 2$ and 80% at $t + 3$ before Covid-19 to 8.8% at $t + 2$ and $t + 3$ after the pandemic. Similarly, this disruption affected the distributor, and the operational status of the distributor at $t + 3$ and $t + 4$ decreased to 54.3% and 53.9%, i.e. 33.9% and 33.6% compared to the time when Supplier 1 was not disrupted. According to the proposed model, to quantify the ripple effect caused by the supply disruption in the present research and according to the foregoing, the ripple effect caused by this disruption in the amount of sales lost during this period can be observed quantitatively.

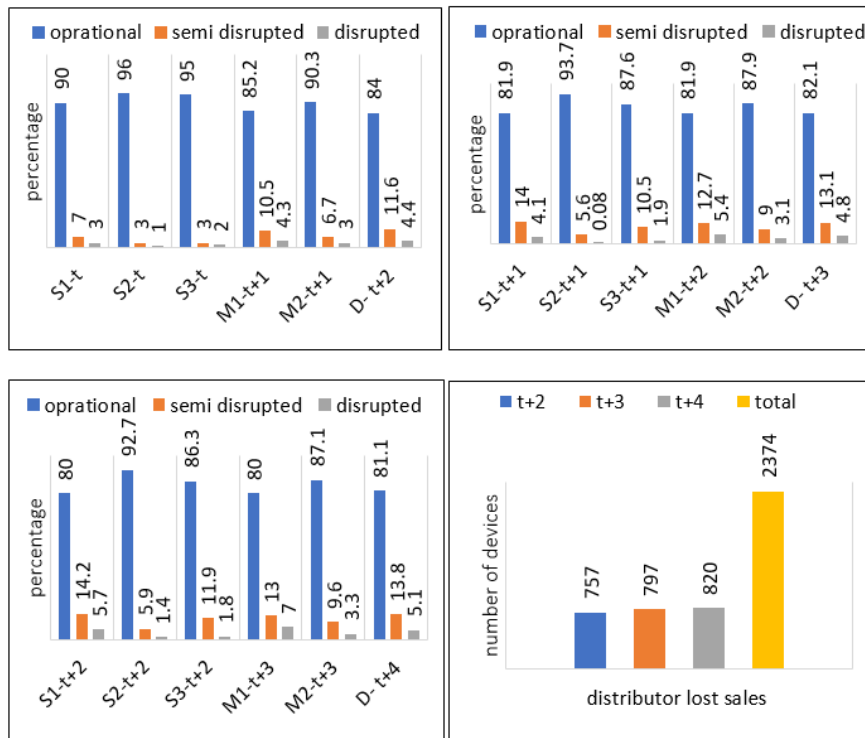


Figure 10. The distribution probabilities of suppliers, manufacturers and distributors and lost sales for the distributor over three time periods.

Before disruption in Supplier 1, the total amount of lost sales for the distributor at $t + 3$ and $t + 4$ period was 797 and 820 devices, which increased by almost 80% and 76.5% to 1434 and 1447 devices after the disruption, respectively. The total number of sales lost after Covid-19 disruption during this quarter has reached 3638 devices, which increased by 53.2% as compared to the pre-pandemic period.

4.3. Comparing the model prediction with what happened after the supply chain disruption

Practically, the situation in this supply chain can be seen that Supplier 1 was disrupted at $t + 1$ and $t + 2$ after the Covid-19 outbreak in China, and failed to meet its obligations. Regarding this disruption, Supplier 1, Manufacturer 1 at $t+2$ and $t+3$ and the distributor at $t+3$ and $t+4$ could not reach the previously predicted operation condition before the disruption. Finally, the distributor could sell 2350 and 2230 devices at $t+3$ and $t+4$, respectively. The distributor could also sell 3710 devices at $t+2$ where there was no disruption. It can be correctly understood that the presentation model can provide a near-realistic prediction after comparing the amount of lost sales predicted for the distributor before and after the Covid-19 period using the related model with the actual sales status after the pandemic (Figure 12).

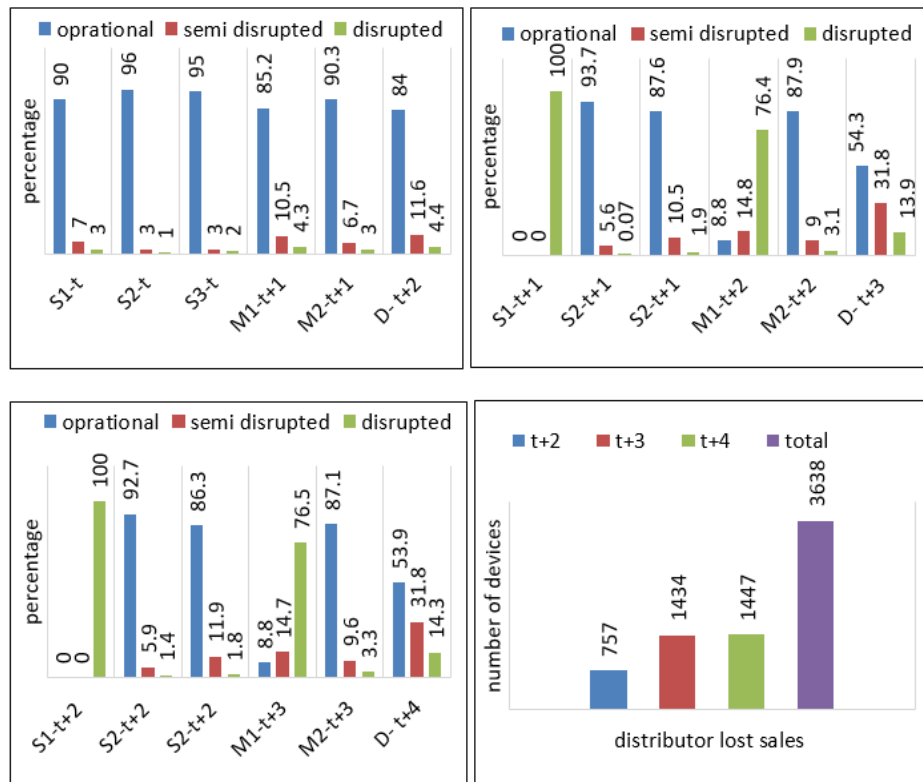


Figure 11. The distribution probabilities of suppliers, manufacturers and distributors and lost sales for the distributor over three time periods during the Covid-19.

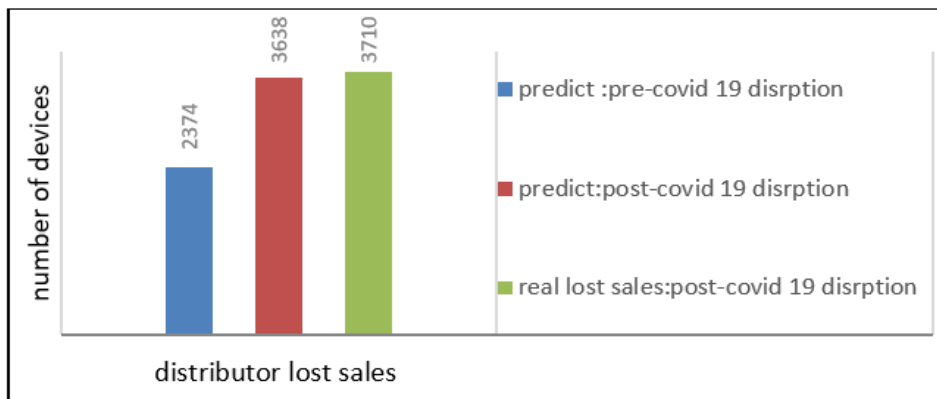


Figure 12. Comparison of lost sales predicted for pre- and post-Covid-19 disruption with the real sale status after the pandemic.

4.4. Analysis of supply chain sensitivity towards suppliers

To achieve a better understanding of the distributor's influence on the suppliers in the examined supply chain, we establish three scenarios: 100% disruption of the first supplier at time t ; 100% disruption of the second supplier at time t ; and 100% disruption of the third supplier at time t . Figure 13 illustrates the outcomes of the second scenario (b) in terms of how the other variables change when the second provider experiences a total disruption at time t . Figure 14 compares and draws conclusions based only on the ultimate outcome of the ripple effect created by the three situations, disregarding the diagrams of the other two scenarios. Figure 14 demonstrates that when the second supplier is impacted, lost revenues are larger than when the other two suppliers are impacted. This is typical for this supply chain, since this one supplier serves both firms. Although the likelihood that the third supply is operational (95%) is larger than the probability that the first supplier is operational (90%) at time t , the repercussions of a disruption to the third source are greater than those of the first (Figure 13). This shows that the distributor's operating status after the second supplier, which is shared by both manufacturers, is more dependent on the third supplier than on the first, and that an interruption in this supplier would result in bigger sales losses for the distributor.

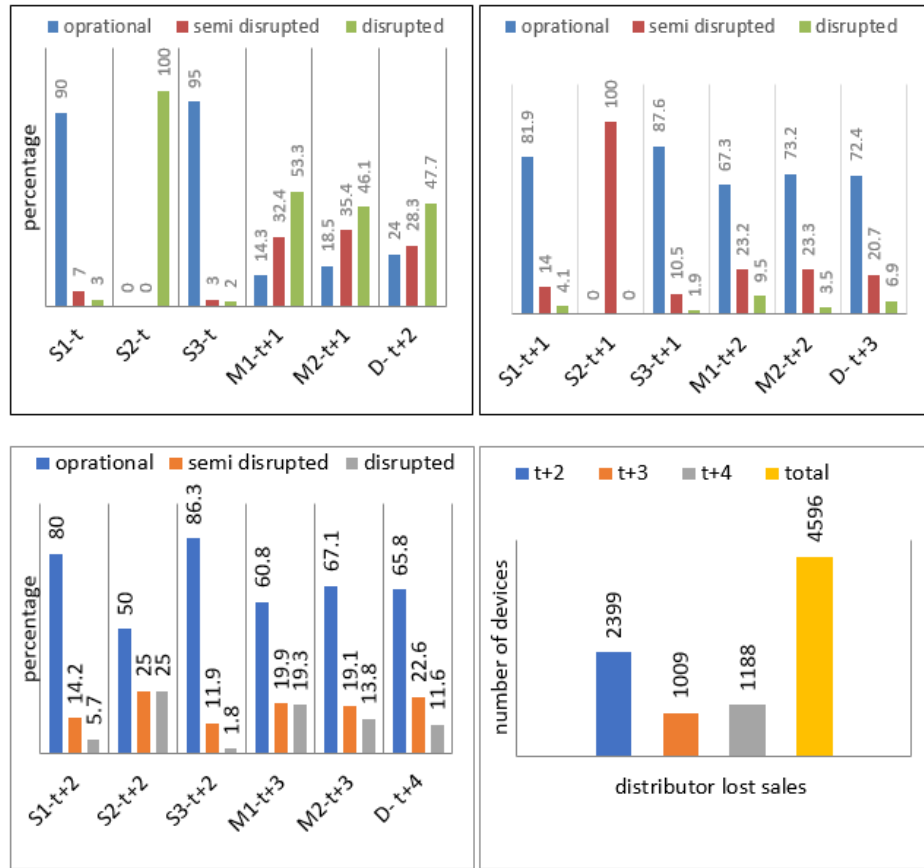


Figure 13. The distribution probabilities of suppliers, manufacturers and distributors and ripple effects of supplier2 disruption on lost sales for the distributor over three time periods.

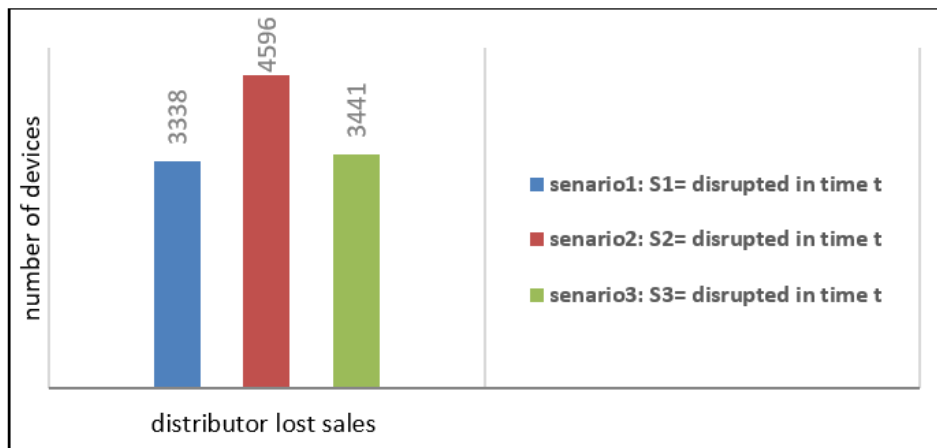


Figure 14. Distributor lost sales in the three defined scenarios.

4.5. Comparing the ripple effect of manufacturer disruption with the ripple effect of supplier disruption

First, we defined a scenario where supplier 1 in time t be disrupted assuming the model designed in Figure 8 and the data in Section 1-4, in order to study the effect of the supplier or manufacturer disruption on the distributor. Figure 15 shows that when supplier 1 is disrupted, the distributor lost sales in all three periods are equal to 3338 systems. Now, we design the model as in Figure 16 in such a way that all conditions proceed as in section 4-1 and the designed model of Figure 8 in order not to change the conditions too much in this comparison; but producer 1 only in period t should depend its initial state of the supply chain on the suppliers, and its state should be determined in the following periods according to the transfer rate of the real data of the supply chain. Table 7 presented the transfer matrix of manufacturer1 according to its dependence on two suppliers by examining 60 periods in the supply chain under study. If in the new designed model (Figure 16) the producer is disrupted in the supply chain period t (materials produced by the supplier at time t are used by the producer at time t+1), the supply chain's lost

sales in three periods reach 3740 systems, as you can see in Figure 17. Figure 18 shows shortly the comparison of the distributor's lost sales. As this study shows, the ripple effect of the disruption to the closer points in the supply chain is greater than when the disruption occurs at a further point in the chain. Any member that is closer to the point of disruption will perceive a bigger blast wave, because if a disruption occurs in a superior member of the chain, the other units will absorb part of the disruption because of their flexibility and resilience. This disruption effect will be smaller at the end of the chain, assuming that the disruption occurs only at one point or in one unit of the supply chain. If the disruption is all pervasive and involves several members of the chain simultaneously, the situation may be different.

Table 7. Conditional probability table (CPT) transition for manufacturer1 in three states.

t	t+Δt		
	Operational	Semi disrupted	Disrupted
Operational	0.905	0.085	0.01
Semi disrupted	0.585	0.18	0.235
Disrupted	0.125	0.75	0.125

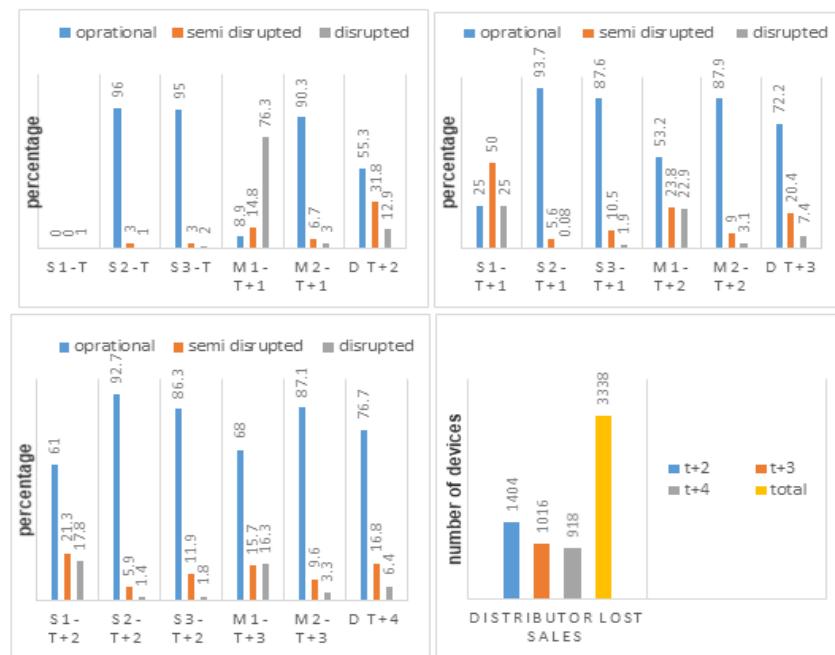


Figure 15. The distribution probabilities of suppliers, manufacturers and distributors and lost sales for the distributor over three time periods during the disruption supplier1.

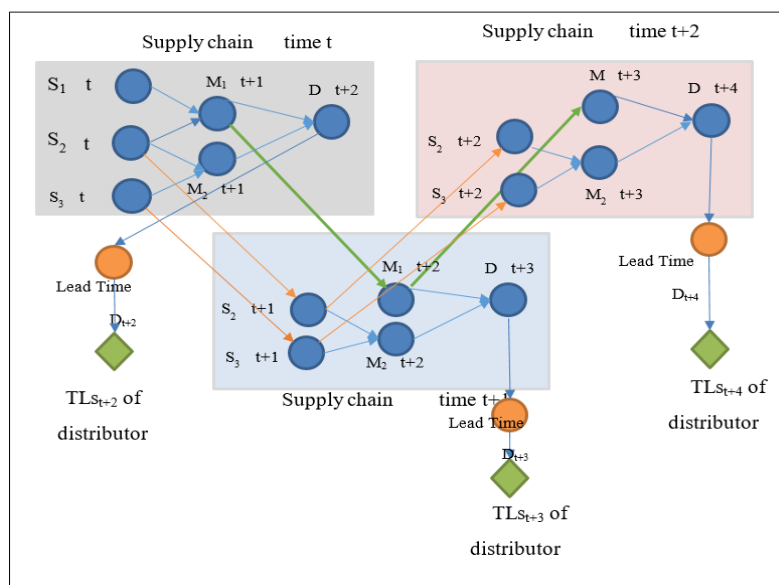


Figure 16. DBN model for evaluating the manufacturer1 disruption ripple effect.

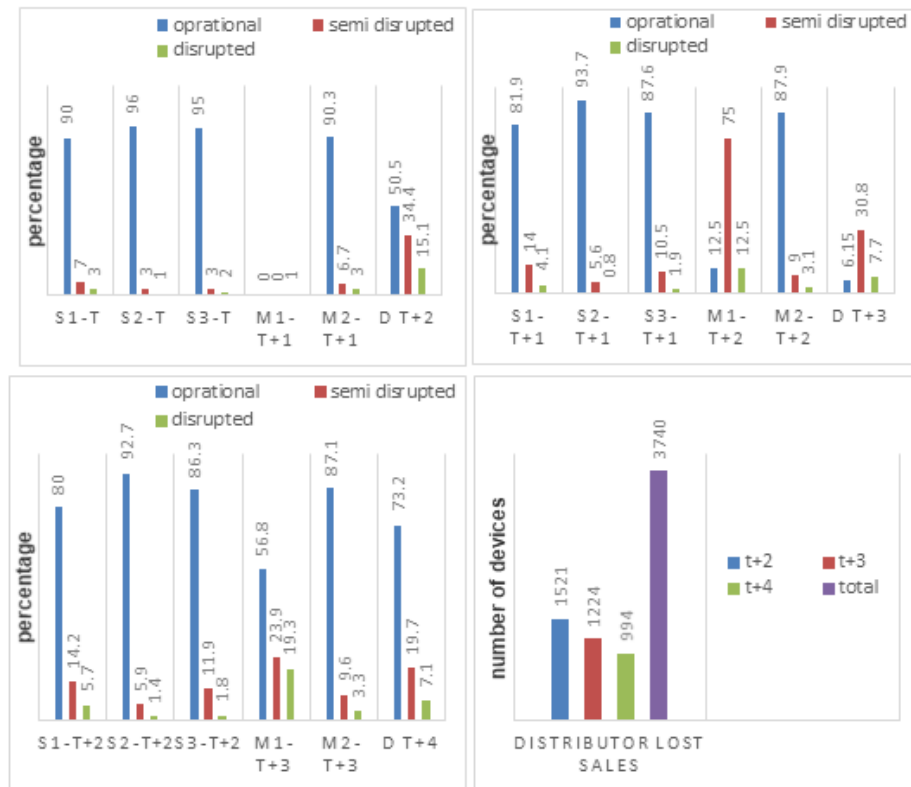


Figure 17. The distribution probabilities of suppliers, manufacturers and distributors and lost sales for the distributor over three time periods during the disruption manufacturer1.

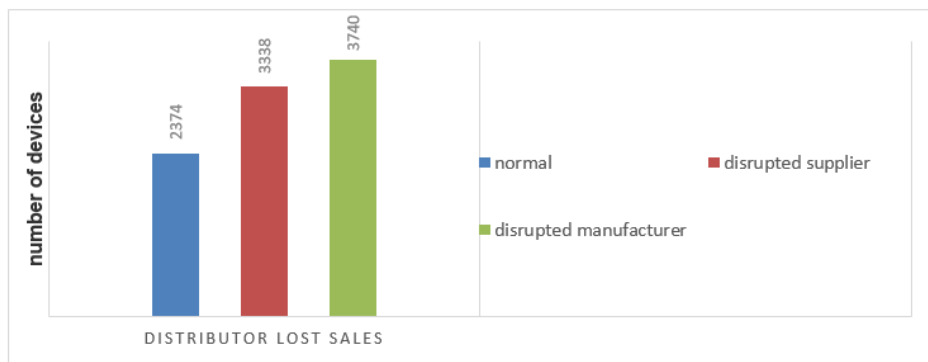


Figure 18. Comparison of lost sales predicted during manufacturer disruption with supplier disruption.

5. Conclusions

In this research we integrated DTMC and DBN as a model and examine the cascading effects of a supply disruption along the whole supply chain. The Markov-discrete-time model that we suggested has three states: operational, semi-disrupted, and disrupted. Different levels of supplier or manufacturer capacity are represented by each state. After integrating the Markov model into the DBN, the disruption propagation was simulated. It was shown that the manufacturer and distributor are impacted when a supplier is disrupted and a node's status is altered. The ripple impact of a multi-stage supply chain interruption is mitigated by evaluating both the supplier's susceptibility and recovery capability. We developed a model that combines a DTMC with a DBN in order to reduce the ripple effect. We presented a criteria that measures the supplier disruption's rippling impact on the producer and distributor in terms of lead time and lost revenue. The suggested ripple impact criteria was applied to and investigated in a case study. Results demonstrate that our approach can be useful for identifying hidden risk pathways in SC, examining the effects of SC disruption and its spread, and ranking potential policies and recovery measures. Our model shows that when a disruption occurs in the upstream of the chain, its effect spreads to the downstream, affects the performance of the chain and causes a decrease in sales or an increase in lost sales. We also presented the manufacturer disruption model, compared the ripple effect of the manufacturer disruption with the ripple effect of the supplier disruption, and showed that each member closer to the disruption point perceives a larger blast wave. There are several suggestions for relevant future research. We provided criteria for dynamically measuring the ripple influence of a supplier disruption over the producer and distributor in aspect of the lead time and

lost sales. The ripple influence may also be quantified using other SC performance measures, such as the opportunity cost. Additionally, the vulnerability of SCSs with conditional probability tables (CPTs) and fixed transition rates was investigated over a time horizon, whereas CPTs and transition rates can be considered for each period with different topologies and time conditions and the ripple effect can be investigated. In the current work, a three-stage SC was examined. Future research might study the effect of disruption propagation in a four-stage supply chain by focusing on retailers. Variable inventory policies are not considered in this study, which can have a significant effect on the ripple effect. Also, only the supply chain nodes (supplier, manufacturer and distributor) have been considered in the presented DBN, while, the supplier status can be measured according to the effect of disruption triggers on it and using BN.

References

- Barua, S., Gao, X., Pasman, H., & Mannan, M. S. (2016). Bayesian Network Based Dynamic Operational Risk Assessment. *Journal of Loss Prevention in the Process Industries*, 41, 399–410. <https://doi.org/10.1016/j.jlp.2015.11.024>
- Brusset, X., Davari, M., Kinra, A., & La Torre, D. (2022). Modelling ripple effect propagation and global supply chain workforce productivity impacts in pandemic disruptions. *International Journal of Production Research*, 2022, 1-20. <https://doi.org/10.1080/00207543.2022.2126021>
- Bruuset, X., Ivanov, D., Jebali, I., & Torre, L.D. (2023). A dynamic approach to supply chain reconfiguration and ripple effect analysis in a epidemic. *International Journal of Production Economics*. <https://doi.org/10.1016/j.ijpe.2023.108935>
- Burgos, D., & Ivanov, D. (2021). Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review*, 152, 102412. <https://doi.org/10.1016/j.tre.2021.102412>
- Cai, B., Liu, Y., & Fan, Q. (2016). A multiphase dynamic Bayesian networks methodology for the determination of safety integrity levels. *Reliability Engineering and System Safety*, 150, 105-115. <https://doi.org/10.1016/j.ress.2016.01.018>
- Chauhan, V. K., Perera, S., & Brintrup, A. (2021). The relationship between nested patterns and the ripple effect in complex supply networks. *International Journal of Production Research*, 59(1), 325-341. <https://doi.org/10.1080/00207543.2020.1831096>
- Chen, J., Wang, H., & Zhong, R. Y. (2021). A supply chain disruption recovery strategy considering product change under COVID-19. *Journal of Manufacturing Systems*, 60, 920-927. <https://doi.org/10.1016/j.jmsy.2021.04.004>
- Constantinou, A. C., Fenton, N., & Neil, M. (2016). Integrating expert knowledge with data in Bayesian networks: Preserving data-driven expectations when the expert variables remain unobserved. *Expert Systems with Applications*, 56, 197-208. <https://doi.org/10.1016/j.eswa.2016.02.050>
- Deleris, L. A., & Erhun, F. (2005). Risk management in supply networks using Monte-Carlo simulation. In: *The Proceedings of the Winter Simulation Conference*, IEEE.
- Dolgui, A., Ivanov, D., & Rozhkov, M. (2020). Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain. *International Journal of Production Research*, 58(5), 1285-1301. <https://doi.org/10.1080/00207543.2019.1627438>
- Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. *International Journal of Production Research*, 56(1,2), 414-430. <https://doi.org/10.1080/00207543.2017.1387680>
- Dong, Z., He, Y., Wang, H., & Wang, L. (2020). Is there a ripple effect in environmental regulation in China? -Evidence from the local-neighborhood greentech innovation perspective. *Ecological Indicators*, 118, 106773. <https://doi.org/10.1016/j.ecolind.2020.106773>
- Duong, A. T. B., Pham, T., Truong Quang, H., Hoang, T. G., McDonald, S., Hoang, T.-H., & Pham, H. T. (2023). Ripple effect of disruptions on performance in supply chains: an empirical study. *Engineering, Construction and Architectural Management*. <https://doi.org/10.1108/ECAM-10-2022-0924>
- Ghadge, A., Er, M., Ivanov, D., & Chaudhuri, A. (2022). Visualisation of ripple effect in supply chains under long-term, simultaneous disruptions: a system dynamics approach. *International Journal of Production Research*, 60(20), 6173-6186.
- Gholami-Zanjani, S. M., Jabalameli, M. S., Klibi, W., & Pishvaei, M. S. (2021). A robust location-inventory model for food supply chains operating under disruptions with ripple effects. *International Journal of Production Research*, 59(1), 301-324. <https://doi.org/10.1080/00207543.2020.1834159>
- He, J., Alavifard, F., Ivanov, D., & Jahani, H. (2019). A real-option approach to mitigate disruption risk in the supply chain. *Omega*, 88, 133-149. <https://doi.org/10.1016/j.omega.2018.08.008>
- Hosseini, S., Al Khaled, A., & Sarder, M. D. (2016). A general framework for assessing system resilience using Bayesian networks: A case study of sulfuric acid manufacturer. *Journal of Manufacturing Systems*, 41, 211-227. <https://doi.org/10.1016/j.jmsy.2016.09.006>
- Hosseini, S., & Barker, K. (2016a). A Bayesian network model for resilience-based supplier selection. *International Journal of Production Economics*, 180, 68-87. <https://doi.org/10.1016/j.ijpe.2016.07.007>
- Hosseini, S., & Barker, K. (2016b). Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports. *Computers and Industrial Engineering*, 93, 252-266. <https://doi.org/10.1016/j.cie.2016.01.007>

- Hosseini, S., & Ivanov, D. (2021). A multi-layer Bayesian network method for supply chain disruption modelling in the wake of the COVID-19 pandemic. *International Journal of Production Research*. <https://doi.org/10.1080/00207543.2021.1953180>
- Hosseini, S., & Ivanov, D. (2020). Bayesian networks for supply chain risk, resilience and ripple effect analysis: A literature review. *Expert systems with applications*, 161, 113649. <https://doi.org/10.1016/j.eswa.2020.113649>
- Hosseini, S., & Ivanov, D. (2019). A new resilience measure for supply networks with the ripple effect considerations: A Bayesian network approach. *Annals of Operations Research*. <https://doi.org/10.1007/s10479-019-03350-8>
- Hosseini, S., Ivanov, D., & Dolgui, A. (2020). Ripple effect modelling of supplier disruption: integrated Markov chain and dynamic Bayesian network approach. *International Journal of Production Research*, 58(11), 3284-3303. <https://doi.org/10.1080/00207543.2019.1661538>
- Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, 125, 285-307. <https://doi.org/10.1016/j.tre.2019.03.001>
- Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering and System Safety*, 145, 47-61. <https://doi.org/10.1016/j.res.2015.08.006>
- Hosseini, S., & Sarder, M. D. (2019). Development of a Bayesian network model for optimal site selection of electric vehicle charging station. *International Journal of Electrical Power and Energy Systems*, 105, 110-122. <https://doi.org/10.1016/j.ijepes.2018.08.011>
- Ivanov, D. (2021a). Supply Chain Risks, Disruptions, and Ripple Effect. In D. Ivanov (ed.), *Introduction to Supply Chain Resilience: Management, Modelling, Technology*. Springer International Publishing, https://doi.org/10.1007/978-3-030-70490-2_1
- Ivanov, D. (2021b). Supply chain viability and the COVID-19 pandemic: A conceptual and formal generalisation of four major adaptation strategies. *International Journal of Production Research*, 59(12), 3535-552. <https://doi.org/10.1080/00207543.2021.1890852>
- Ivanov, D. (2020a). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review*, 136, 101922. <https://doi.org/10.1016/j.tre.2020.101922>
- Ivanov, D. (2020b). Viable supply chain model: integrating agility, resilience and sustainability perspectives – lessons from and thinking beyond the COVID-19 pandemic. *Annals of operations research*. <https://doi.org/10.1007/s10479-020-03640-6>
- Ivanov, D. (2018). OR/MS Methods for Structural Dynamics in Supply Chain Risk Management. In: D. Ivanov (ed.), *Structural Dynamics and Resilience in Supply Chain Risk Management*. Springer International Publishing. https://doi.org/10.1007/978-3-319-69305-7_5
- Ivanov, D. (2017). Simulation-based ripple effect modelling in the supply chain. *International Journal of Production Research*, 55(7), 2083-2101. <https://doi.org/10.1080/00207543.2016.1275873>
- Ivanov, D., & Dolgui, A. (2021a). Stress testing supply chains and creating viable ecosystems. *Operations Management Research*. <https://doi.org/10.1007/s12063-021-00194-z>
- Ivanov, D., & Dolgui, A. (2021b). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. *International Journal of Production Economics*, 232, 107921. <https://doi.org/10.1016/j.ijpe.2020.107921>
- Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International Journal of Production Research*, 58(10), 2904-2915. <https://doi.org/10.1080/00207543.2020.1750727>
- Ivanov, D., Dolgui, A., & Sokolov, B. (2019). Ripple effect in the supply chain: Definitions, frameworks and future research perspectives. In: *Handbook of ripple effects in the supply chain* Springer. Cham. https://doi.org/10.1007/978-3-030-14302-2_1
- Ivanov, D., Dolgui, A., Sokolov, B., & Ivanova, M. (2017). Literature review on disruption recovery in the supply chain. *International Journal of Production Research*, 55(20), 6158-6174. <https://doi.org/10.1080/00207543.2017.1330572>
- Jingzhe, C., Hongfen, W., & Ray, Y. Z. (2022). A supply chain disruption recovery strategy considering product change under COVID-19. *Journal of Manufacturing Systems*, 60, 920-927.
- Jones, M. T. (2005). Estimating Markov transition matrices using proportions data: an application to credit risk. (November 2005). IMF Working Paper No. 05/219. <https://ssrn.com/abstract=888088>
- Kinra, A., Ivanov, D., Das, A., & Dolgui, A. (2020). Ripple effect quantification by supplier risk exposure assessment. *International Journal of Production Research*, 58(18), 5559-5578. <https://doi.org/10.1080/00207543.2019.1675919>
- Li, Y., Chen, K., Collignon, S., & Ivanov, D. (2021). Ripple Effect in the Supply Chain Network: Forward and Backward Disruption Propagation, Network Health and Firm Vulnerability. *European Journal of Operational Research*, 291(3), 1117-1131. <https://doi.org/10.1016%2Fj.ejor.2020.09.053>
- Llaguno, A., Mula, J., & Campuzano-Bolarin, F. (2022). State of the art, conceptual framework and simulation analysis of the ripple effect on supply chains. *International Journal of Production Research*, 60(6), 2044-2066. <https://doi.org/10.1080/00207543.2021.1877842>

- Liu, M., Liu, Z., Chu, F., Zheng, F., & Chu, C. (2021). A New Robust Dynamic Bayesian Network Approach for Disruption Risk Assessment under the Supply Chain Ripple Effect. *International Journal of Production Research*, 59(1), 265-285. <https://doi.org/10.1080/00207543.2020.1841318>
- Lohmer, J., Bugert, N., & Lasch, R. (2020). Analysis of resilience strategies and ripple effect in blockchain-coordinated supply chains: An agent-based simulation study. *International Journal of Production Economics*, 228, 107882. <https://doi.org/10.1016/j.ijpe.2020.107882>
- Marcot, B. G., & Penman, T. D. (2019). Advances in Bayesian network modelling: Integration of modelling technologies. *Environmental Modelling and Software*, 111, 386-393. <https://doi.org/10.1016/j.envsoft.2018.09.016>
- Mishra, D., Dwivedi, Y. K., Rana, N. P., & Hassini, E. (2021). Evolution of supply chain ripple effect: a bibliometric and meta-analytic view of the constructs. *International Journal of Production Research*, 59(1), 129-147. <https://doi.org/10.1080/00207543.2019.1668073>
- Özçelik, G., FarukYılmaz, Ö., & BetülYeni, F. (2021). Robust optimisation for ripple effect on reverse supply chain: an industrial case study. *International Journal of Production Research*, 59(1), 245-264. <https://doi.org/10.1080/00207543.2020.1740348>
- Park, Y. W., Blackhurst, J., Paul, C., & Scheibe, K. P. (2022). An analysis of the ripple effect for disruptions occurring in circular flows of a supply chain network. *International Journal of Production Research*, 60(15), 4693-4711. <https://doi.org/10.1080/00207543.2021.1934745>
- Pournader, M., Kach, A., & Talluri, S. (2020). A review of the existing and emerging topics in the supply chain risk management literature. *Decision Sciences*, 51(4), 867-919. <https://doi.org/10.1111/dec.12470>
- Qazi, A., Dickson, A., Quigley, J., & Gaudenzi, B. (2018). Supply chain risk network management: A Bayesian belief network and expected utility-based approach for managing supply chain risks. *International Journal of Production Economics*, 196, 24-42. <https://doi.org/https://doi.org/10.1016/j.ijpe.2017.11.008>
- Queiroz, M. M., Ivanov, D., Dolgui, A., & FossoWamba, S. (2020). Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research*. <https://doi.org/10.1007/s10479-020-03685-7>
- Rebello, S., Yu, H., & Ma, L. (2018). An integrated approach for system functional reliability assessment using Dynamic Bayesian Network and Hidden Markov Model. *Reliability Engineering and System Safety*, 180, 124-135. <https://doi.org/10.1016/j.ress.2018.07.002>
- Rodger, J. A. (2014). Application of a fuzzy feasibility Bayesian probabilistic estimation of supply chain backorder aging, unfilled backorders, and customer wait time using stochastic simulation with Markov blankets. *Expert Systems with Applications*, 41(16), 7005-7022. <https://doi.org/10.1016/j.eswa.2014.05.012>
- Ruel, S., El Baz, J., Ivanov, D., & Das, A. (2021). Supply chain viability: conceptualization, measurement, and nomological validation. *Annals of Operations Research*. <https://doi.org/10.1007/s10479-02103974-9>
- Sindhvani, R., Jayaram, J., & Saddikuti, V. (2022). Ripple effect mitigation capabilities of a hub and spoke distribution network: an empirical analysis of pharmaceutical supply chains in India. *International Journal of Production Research*. <https://doi.org/10.1080/00207543.2022.2098073>
- Singh, S., Kumar, R., Panchal, R., & Kumar Tiwari, M. (2021). Impact of COVID-19 on logistics systems and disruptions in food supply chain. *International Journal of Production Research*, 59(7), 1993-2008. <https://doi.org/10.1080/00207543.2020.1792000>
- Sokolov, B., Ivanov, D., Dolgui, A., & Pavlov, A. (2016). Structural quantification of the ripple effect in the supply chain. *International Journal of Production Research*, 54(1), 152-169. <https://doi.org/10.1080/00207543.2015.1055347>
- Song, B., Lee, C., & Park, Y. (2013). Assessing the risks of service failures based on ripple effects: A Bayesian network approach. *International Journal of Production Economics*, 141(2), 493-504. <https://doi.org/10.1016/j.ijpe.2011.12.010>
- Wan, C., Yan, X., Zhang, D., Qu, Z., & Yang, Z. (2019). An advanced fuzzy Bayesian-based FMEA approach for assessing maritime supply chain risks. *Transportation Research Part E: Logistics and Transportation Review*, 125, 222-240. <https://doi.org/10.1016/j.tre.2019.03.011>
- Yoon, J., Talluri, S., Yildiz, H., & Ho, W. (2018). Models for supplier selection and risk mitigation: a holistic approach. *International Journal of Production Research*, 56(10), 3636-3661. <https://doi.org/10.1080/00207543.2017.1403056>
- Zhang, Y., Zhao, C., & Pang, B. (2018). Budget allocation in coping with supply chain disruption risks. *International Journal of Production Research*, 56(12), 4152-4167. <https://doi.org/10.1080/00207543.2018.1430905>