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| RESEARCH ARTICLE

Innovative Simulation Model for Analyzing the Effects of Supplier Disruptions on Supply Chain Distributors

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| ABSTRACT

In the current business landscape, supply chain disruptions, have become increasingly prevalent, impacting operational efficiency and profitability. These disruptions have resulted in significant ripple effects throughout the supply chain, resulting in increased delivery times and lost sales that, in extreme cases, can reach Statistics up to 76,169 units. Despite the growing recognition of the importance of managing these disruptions, comprehensive models that quantitatively assess their propagation and impact on downstream distributors are lacking. This study aims to address this gap by developing a discrete-time Markov chain model integrated with a Baye.sian network to analyze the ripple effects of supplier disruptions on distributors. The research focuses on key metrics such as lead times and lost sales, revealing that disruptions can increase lost sales by up to 44% in definite scenarios. By employing this dynamic modeling approach, the study illustrates the pathways through which disruptions propagate, identifies critical risk factors, and evaluates supplier vulnerabilities. The findings underscore the necessity for robust supply chain strategies to mitigate the effects of disruptions, providing valuable insights for managers to make informed decisions regarding supplier selection and inventory management. The scientific implications of this research contribute to the evolution of more comprehensive frameworks for disruption management in multi-tier supply chains, paving the way for future studies to expand on these insights and enhance supply chain resilience.

| KEYWORDS

Supplier Disruptions, Supply Chain, Simulation Model, Ripple Effect, Distributors

| ARTICLE INFORMATION

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1- Introduction

The current business environment has led to high uncertainty and chaotic behavior in the supply chain. In the contemporary world, supply chains face numerous challenges, ranging from uncertainty to disordered behavior (Abadi et al., 2015). The outbreak of the COVID-19 virus clearly showed how vulnerable supply chains are and how a disruption can affect the performance of the entire chain. Given the importance of supply chain management for organizations in these conditions, it is very necessary (Hani, 2022) and significant to predict and achieve the essential adaptability to cope with or prevent the emergence of disruption (Levner & Ptuskin, 2018). These crises not only lead to a decrease in service quality and a drop in sales but also affect relationships with suppliers and lead to distrust (Dong et al., 2020). Effective supply chain management and risk prediction are significant for maintaining efficiency and achieving organizational goals. Research in this area helps managers design appropriate strategies to reduce the consequences of disruptions in supply chains and build the necessary resilience against crises **(**Li et al., 2021).

One of the main challenges for supply chain managers is the inability to predict and manage the effects of these disruptions. In particular, the occurrence of disruptions spreading in a wave from suppliers to other parts of the chain requires more detailed investigation and modeling. This uncertainty and the inability to identify and assess the risks arising from disruptions can affect supply chain objectives, including efficiency and responsiveness (Chauhan et al., 2021).

Previous research has shown that these disruptions have grave effects on supply chain performance, such that reduced service quality, delayed delivery of goods, and reduced sales are among their consequences (Beske et al., 2014). At the same time, many studies have examined the overall effects of disruptions and have not paid much attention to the specifics of how these effects spread through the supply chain (Marques et al., 2021). In particular, the principle of the ripple effect, which refers to the spread of disruptions from suppliers to other parts of the chain, has rarely been explored (Haeri et al., 2020). It represents a fundamental research gap, as a complete understanding of how disruptions propagate can help managers make better decisions and design more effective strategies to reduce the vulnerability of supply chains (Shi et al., 2022).

However, there is a need for a comprehensive framework for analyzing and managing the effects of these disruptions. In particular, given that disruptions in the supply chain are inevitable, identifying and assessing their effects helps managers design effective strategies to reduce the Weakness of the chain and accelerate the recovery process **(**Park et al.,2022). A new theory addressing the research gap in supply chain management focuses on the ripple effect, which examines how disruptions in one part of the supply chain (Shafique and Rahman, 2017).can impact other areas**.** This concept highlights the interconnectedness of supply chain components and emphasizes the need for strategies to manage these cascading effects effectively (de Vasconcelos et al., 2021).

This theory suggests that it is necessary to more precisely examine how disruptions propagate from suppliers to other parts of the supply chain. Using analytical and quantitative models, this theory can help managers more effectively assess risks and design appropriate strategies to reduce the pessimistic effects of disruptions. This new approach helps to gain clarity and manage the resilience of supply chains in the face of uncertainty and crises. Supply chain research has extensively studied supplier disruptions and the Ripley effect. However, a notable gap exists in understanding how disruptions propagate and their impact on distributors within multi-level supply chains. Addressing this gap is essential for improving decision-making in supply chain management, which directly influences organizational efficiency and profitability. Therefore, this study aims to develop a hybrid model based on discrete Markov chains and Bayesian networks that can quantitatively assess the risks of disruptions and help managers choose appropriate strategies to reduce the speed of disruption propagation and improve supply chain efficiency.

2- Literature review

Ivanov et al. (2019) addressed the strategic issue for any company deciding on its supply chain configuration (equipment positioning, customer allocation, and disruptions in the supply chain for a centralized manufacturing system (Ivanov et al., 2019).

In recent years, supply chain disruptions have resulted from the emergence of complex and interconnected networks coupled with the widespread implementation of demand-driven manufacturing strategies. Zhao et al. (2022) have addressed supply chain disruptions that significantly affect supply chain performance and often impose Weighty costs on the supply chain (Zhao et al., 2022). Teuteberg and Wittstruck. (2010), Lean manufacturing and the increasing reliance on just-in-time production, combined with uncertainty in dynamic systems, have increased system vulnerability and brought the issue of disruptions to the forefront (Teuteberg & Wittstruck, 2010). Hosseini et al. (2020) The unpredictability of disruptions and the magnitude of the consequences of supply chain disruption propagation have driven a recent wave of research focusing on the ripple effect of disruptions (Hosseini et al., 2020). Ivanov et al. (2019) reported that downstream diffusion results in decreased demand fulfillment because of the ripple effect. Supply chain management can create interdependencies in a collection of patterns (Ivanov et al., 2019). Shi et al,. (2022) have examined the slow flow of goods between manufacturers and distribution centers, which is vulnerable to multiple disruptions and risks (Shi et al ., 2022). Hsu et al. (2022) Different categories of dislocations in supply, production, and logistics play an important role in monitoring supply chain risk and power patterns (Hsu et al., 2022). Most research focused on supply chain disruptions has shown that increasing flexibility and designing a resilient supply chain are essential strategies to prevent and mitigate the effects of disruptions. Ali et al. (2021) suggested strengthening facilities and anticipating backup capacities as pre-disruption measures (Ali et al., 2021). While post-disruption strategies involve planning to recover lost capacity and adapt to disruption conditions, Enrique et al. (2022) have examined the increasing complexity and interconnectedness of supply networks and the adoption of demand-driven production methods, making supply chains more vulnerable to disruption (Enrique et al ., 2022). Ivanov et al. (2021) have addressed the creation of flexibility in the supply chain, including various strategies, such as transportation flexibility, the use of diverse suppliers, and the expansion of social responsibility initiatives (Ivanov et al., 2021). Feizabadi et al. (2021) noted the challenges associated with making decisions about supply chain configuration (Feizabadi et al., 2021). Juan et al. (2022) also examined the effects of disruptions on supply chain performance (Juan et al., 2022). Park et al. (2022) introduced the concept of the ripple effect (Park et al., 2022). Maharjan and Kato (2022) pointed out the importance of designing flexible and resilient supply chains (Maharjan & Kato, 2022). El Baz and Ruel (2021) noted the role of disruption impacts on supply chains (El Baz & Ruel, 2021). Ghadge et al. (2022) examined the consequences of long-term and simultaneous disruptions caused by COVID-19 through a dynamic systems simulation approach (Ghadge et al., 2022). Carter et al. (2011) and Closs et al. (2011) The primary objective of the research was to highlight the benefits of dynamic systems approaches in identifying and demonstrating the ripple effect and analyzing the dynamic behaviors of production and supply at different levels of the supply chain, which examined four disruption techniques arising from market risks, supply chain logistics, and their simultaneous combinations (Carter et al., 2011); (Closs et al., 2011). Mirzaei et al. (2024) conducted a study titled Presenting a Model of Key Success Factors to Deal with the Wave Effect in the Machine-made Carpet Supply Chain in Iran with the tendency toward the Covid-19 pandemic (Mirzaei et al., 2024). Brusset et al. (2023) modeled the ripple effect and labor productivity impacts in global supply chains following disruptions caused by the COVID-19 pandemic (Brusset et al., 2023). Yang & Peng, (2023) proposed a supply chain disruption recovery strategy during the COVID-19 pandemic emphasizing product change. (Yang & Peng , 2023). Bussieweke et al. (2024) reviewed a recent paper on the ripple effect (Bussieweke et al., 2024). Sindhwani et al. (2023) worked on ripple effect mitigation capabilities in the Indian pharmaceutical distribution network during disruptions such as the COVID-19 pandemic (Sindhwani et al., 2023).

Research Gap and Novelty

Previous research in the supply chain field has mainly focused on the overall effects of disruptions on supply chain performance and has not explored the details of how these disruptions propagate (**Feizabadi et al., 2021).** In particular, the ripple effect, which refers to the propagation of disruptions from suppliers to other parts of the supply chain, has rarely been considered (Yılmaz et al., 2021). This gap in the literature can lead to managers not fully understanding how disruptions affect supply chain performance and inefficient decision-making. Also, there is a need for more comprehensive analytical models and practical strategies for designing resilient and flexible supply chains.

Based on the literature review and studies conducted in previous research, articles related to the ripple effect of disruption were classified into three categories. The first section reviews the literature and examines the factors that cause the ripple effect and how it spreads. The second group has studied the issue of designing supply chains that are resilient to disruption, such as flexible and resilient chains that reduce the ripple effect of disruption along the chain. The third group has turned to modeling and simulations. Through this, they have assessed the propagation of **disturbance** and the ripple effect of disruption in the supply chain and have attempted to quantitatively show the impact of disruption along the chain using inventory, cost, service level, profit, and other indicators. It introduces the ripple effect theory as a new approach to supply chain management, which examines in more detail how disruptions propagate and their effects on distributors. The **application** of hybrid models, such as Markov chains and Bayesian networks, allows us to quantitatively assess the risks of disruptions and design more effective strategies to reduce the speed of disruption propagation and improve supply chain efficiency. This new approach enhances the understanding of supply chain resilience to uncertainties and crises, enabling managers to make better decisions in supply chain management.

3- Methods

In this section:

A Markov chain model is displayed to simulate the actions of a supplier in the event of a long-term disruption. To introduce the model, we first consider three states for a supplier:

1. An operational state where the supplier operates at full capacity;
2. A state where the supplier loses all capacity due to the severity and magnitude of the disruption and becomes disrupted.
3. A state in which the supplier loses some of its capacity. It is in a semi-disrupted or semi-operational state.

This study considers a semi-operational state when the supplier loses 50% of its capacity in case of a disruption. It is important to note that this may not always be the case in practice. Future studies could consider this state dynamically or represent the Markov model with more than three states to account for various conditions.

Figure 1 shows the Markov chain model. Assuming that a supplier operates under normal conditions before a disruption occurs. If a disruption happens, suppliers can absorb the shock without losing capacity. This scenario depicts the absorption operating mode using its loop in zero mode.

On the other hand, the supplier may lose 50% of its capacity after a disruption occurs. This state changes from state zero to state one with an output arc. In another scenario, if the supplier faces a severe disruption, it may lose all operational capacity. This scenario occurs through a transition from state zero to state two.

Suppose a supplier is semi-disrupted and in state (1) at time t. This supplier can recover its lost capacity by transitioning backward from state (1) at time t to state (0) at time t+1. Otherwise, it may move to the entirely disrupted state (state 2), or it might not be able to recover and remain in the semi-operational state at time t+1.

Finally, consider the case where the supplier is entirely disturbed at time t. The supplier can recover all its lost capacity at time t+1 through an incoming arc from state 2 to state 0, or it may recover 50% of the lost capacity at time t+1 and the remaining

capacity at time t+2. Alternatively, the supplier might remain disrupted at time t+1. This scenario is represented by three outgoing arcs: state 2 to state 1, state 1 to state 0, and state 2 to state 2.
Based on experiences of prolonged disruptions during the COVID-19 pandemic, suppliers, manufacturers, and service providers may be unable to restore capacity for several periods. They may even lose any remaining capacity. Therefore, outgoing arcs from state (1) to state (2), as well as from state 1 to state (1) and from state (2) to state (2), have been considered.
π_o, π_1, π_2 represent the probabilities of the supplier being in states 0, 1, and 2, respectively. The transition rates from one state to another are signified by (μ_3, λ_3, μ_2, μ_1, λ_1, λ_2, γ1, γα, and β). Relationships 1 to 4 are equations written for this model. By solving the following equations:
Determine the supplier's probabilities in states 0, 1, and 2. By knowing the likelihood of each state, the supplier can better understand its vulnerability and define an efficient strategy to mitigate disruptions.

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

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

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

Relationship 4:
$\pi_0 + \pi_1 + \pi_2 = 1$

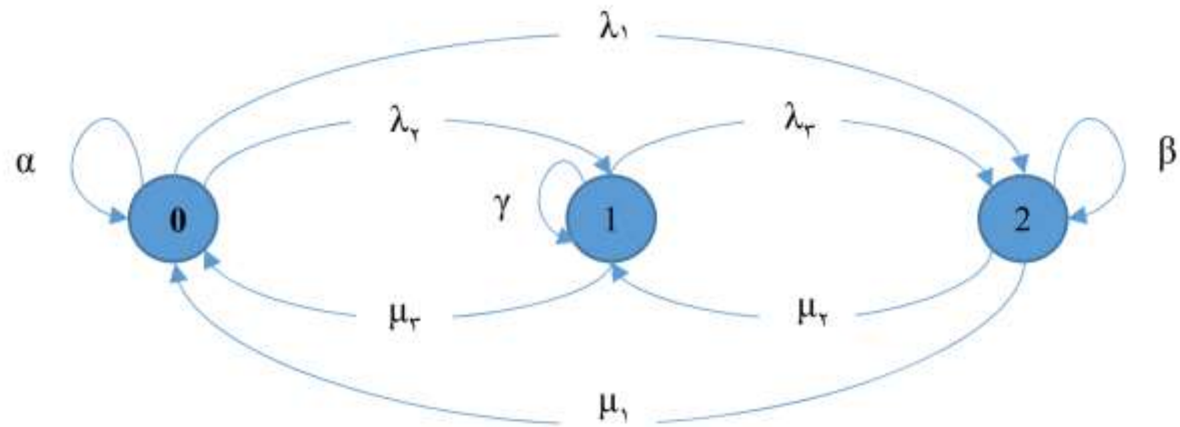

Fig 1: Discrete-Time Markov Chain Model for Supplier Capacity Disruption

4- Results

4-1-Dynamic Bayesian network model

4-1-1-Bayesian network theory

Bayesian networks combine expert knowledge with historical data to quantify risk by documenting causes and effects through a graphical representation. They are also used to address risk management issues.
From a mathematical perspective, Bayesian networks describe directed acyclic graphs with collection variables defined by V = {X1, X2, ..., Xn} and a set of arcs that determine (variables) the interactions between nodes. An arc from X_i to X_j indicates that the value of variable X_j depends on the value of X_i at this location (X_i), and X_j is referred to as the parent and child nodes, respectively. The joint probability of all variables (nodes) was expressed as the product of the conditional probabilities of each node using the chain rule.

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

For example, consider a Bayesian network model with four variables, as shown in Figure 2. X_1 is the root node, X_2 and X_3 are intermediate nodes, and X_4 is the leaf node. Conditional probabilities in Bayesian networks are **employed** to establish causal relationships between variables. The joint probability distribution of Bayesian network models considered the network structure and dependencies between variables. In the example presented, the prior probability $P(X_1)$ and the conditional probabilities $P(X_4|X_2, X_3)$, $P(X_2|X_1)$, and $P(X_3|X_2)$ need to be defined. The joint probability distribution of the Bayesian network model in Figure 2 is determined as follows.

Relationship 6:
$P(X_1, X_2, X_3, X_4) = P(X_1)\, P(X_2|X_1)\, P(X_3|X_2)\, P(X_4|X_2, X_3)$

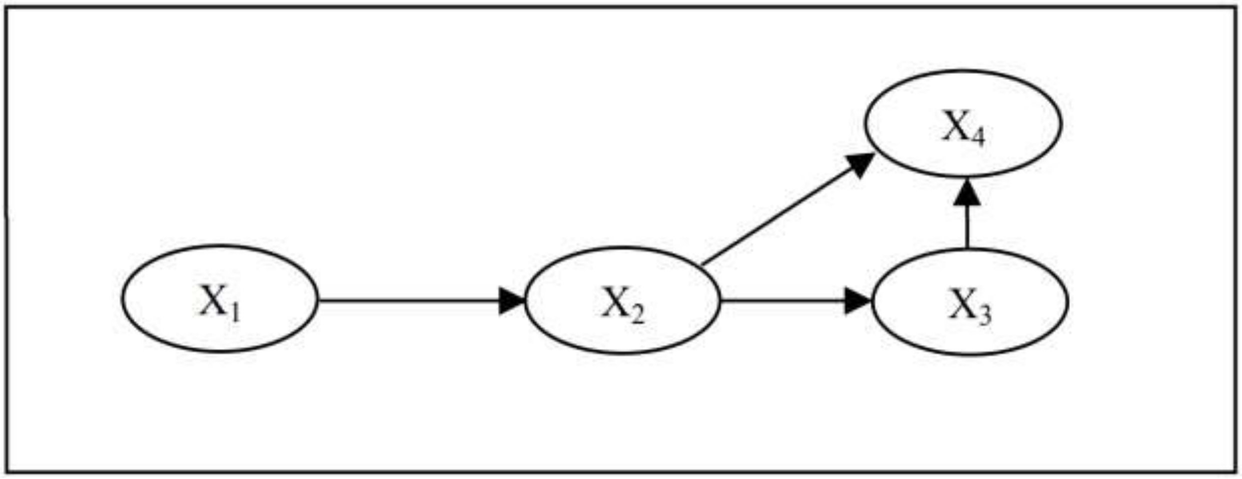

Fig 2: Simple Bayesian Network with 4 Nodes

In a Bayesian network, each variable is relevant with a conditional probability table (CPT), which determines the probability of a variable occurring given the values of other variables.
The Conditional Probability Table can express the conditional probability between two variables. The joint probability distribution (JPD) is employed to determine the probabilities of individual variables within a Bayesian network. Suppose we are looking to compute X_2 .Then $P(X_2)$ can be expressed as follows:

Relationship 7:
$P(X_2) = \left(\sum_{x_1} P(x_1) \left(\sum_{x_3} P(x_3|x_2)\left(\sum_{x_4} P(x_4|x_2, x_3)\right)\right)\right)$

As shown, Equation 7 was revised using the marginalization technique used in Equation 8.
To explain Equation 8 and better understand Bayesian networks, Figure 3 presents a simple Bayesian network with one manufacturer and two suppliers.

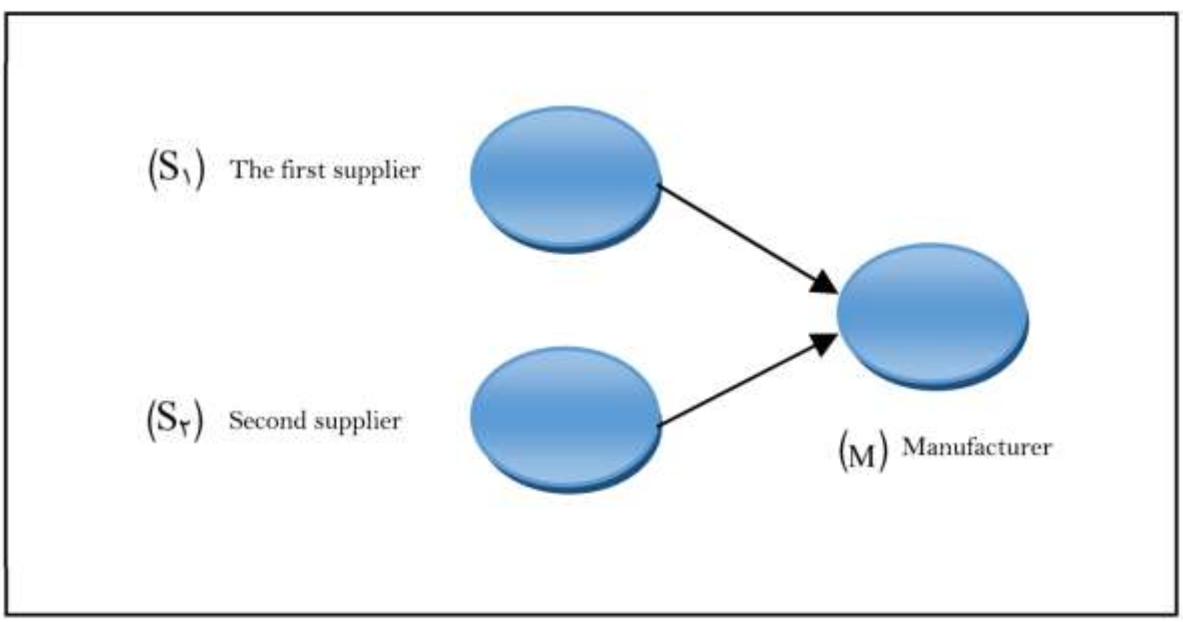

Fig 3. Simple Bayesian network

Equation 9 shows the method of calculating the probability of a manufacturer being in a chaotic state based on the conditional probability table defined between the manufacturer and suppliers. We assume that the two operational and disrupted states in Table (1) do not provide the equations determining the probability of the operational and semi-operational states of the producer here. The distributor status determination relationship in a supply chain creates three layers of conditional probability tables between the distributor and the manufacturer.

Table 1. Table of conditional probabilities of the producer

Supplier 1	Operational		Disturbed	
Supplier 2	Operational	Disturbed	Operational	Disturbed
Manufacturer	Disturbed	Disturbed	Disturbed	Disturbed

Relationship 9:
P (M disrupted)
= $\sum_{S_1, S_2} P\left(M\ disrupted|S_1, S_2\right) + P(M\ disrupted|S_1$
= operational, S_2= operational) × P (S_1 = operational) × P(S_2
= operational) + $P(M\ disrupted|S_1$ = operational, S_2
= $disrupted$) × P (S_1 = operational) × P (S_2
= $disrupted$)+ P ($M\ disrupted|S_1$ = $disrupted, S_2$
= operational) × P (S_1 = $disrupted$) × P (S_2
= operational)
+ P ($M\ disrupted|S_1$ = $disrupted, S_2$= $disrupted$)
× P (S_1 = $disrupted$) × P (S_2 = $disrupted$)

4-2-Dynamic Bayesian network

The simulation occurs in several phases, along with the network's expansion and the time dimension**.** Dynamic Bayesian networks are applied to model a stochastic process in a dynamic environment.
It is a suitable method for capturing the ripple effect caused by supply disturbances because the cascading effect is inherently random and dynamic (Yang & Peng, 2023)**.**
To simplify the modeling process of the ripple effect of a disruption, we consider the following key assumptions:

- The system is time-invariant, meaning the conditional probability tables of producers and distributors remain constant across different periods .
- This process is a discrete-time Markov process, indicating that the probability distribution of the state at time t + 1 depends only on the state at time t and not on the sequence of events that preceded it .
- The transition probability matrix of the suppliers is also assumed to be constant across different periods.

Based on the assumptions, with different periods, the dynamic Bayesian network emerges as an extension of the Bayesian network. Figure 4 shows a simple dynamic Bayesian network that shows the relationship between variables at time t and t+1. The probability of the supplier value distribution occurring at time t+1 depends on its probability distribution at time t. The joint probability distribution of a dynamic Bayesian network in a dynamic environment can be transmitted as follows:

Relationship 10:
P ($X_{1,t}$, $X_{2,t}$, …, $X_{n,t}$) = $\prod_{t=1}^{T}\prod_{i=1}^{N} P(X_{i,t}|X_{1,t}, X_{2,t}, \ldots, X_{i-1,t})$

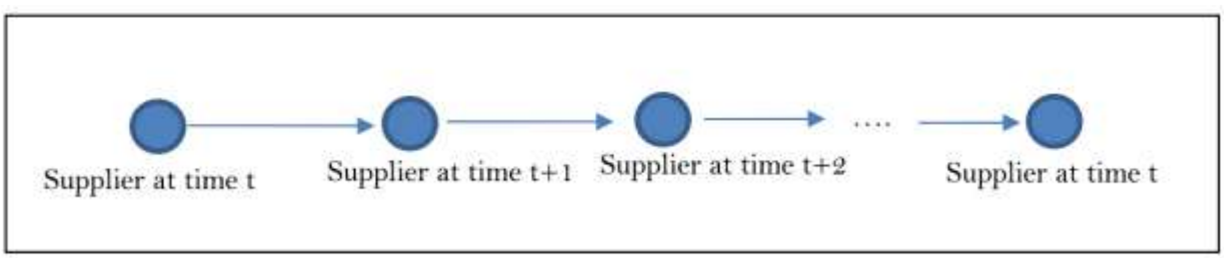

Fig 4. Dynamic Bayesian network of suppliers with periods T

1) *Transition Matrix*

The main challenge in a dynamic Bayesian network system is defining the transition probabilities of the variables over time. The Markov transition probability model begins with a set of discrete states. In this paper, we derive the transition matrix for the case where we identify all states of a supplier within a given time horizon.

Suppose there are discrete categories in R that structure the observations. We can define a transition matrix P=[p_{ij}] as a matrix of probabilities representing the likelihood of state changes. Each part of the matrix P_{ij} indicates the probability of being in state i at time t-1 and transitioning to state j at time t **(Ivanov, 2021).**

Relationship 11:

$$\begin{bmatrix} P_{11} & P_{12}\cdots & P_{1R} \\ P_{21} & P_{22}\cdots & P_{2R} \\ \vdots & \vdots \ \ddots & \vdots \\ P_{R1} & P_{R2} & P_{RR} \end{bmatrix}$$

In general, if (nij) represents the number of times a supplier has been in state (i) at time t -1 and in state j at time t, we can estimate the probability of a supplier - being in state j at time t using Relation 12, given that they were in state (i) at time t - 1. This probability is denoted by (P_{ij}).

Relationship 12:

$$\text{Pij} = \frac{nij}{\sum_j nij}$$

4-3- Wave effect modeling

The bullwhip effect occurs when the impact of a disturbance upstream in the supply chain cannot be localized and spreads downstream, negatively affecting the performance of the supply chain in terms of service level costs and lead times (Zanjani et al., 2021)**.**

The delivery time or lead time is highly dependent on three operational states: operational, semi-operational, and entirely disrupted conditions of the supply chain components (suppliers, manufacturers, and distribution centers), which in turn are influenced by the status of the producers and suppliers. The lead time, denoted in this study as Lt, varies depending on whether the supplier is operational, semi-operational, or completely disrupted. Thus, the variable Lt is related to the status of a supplier from the perspective of the business network. The variable Lt is assumed to have three levels:

- Low
- Medium
- High

Depending on the distributor's circumstances, the goods can be delivered on time to meet customer expectations or with a significant delay, setting a time interval or delivery time.

For example:

Table 2 of this study shows the delivery time variable.

Table 2: Linguistic Variable of Lead Time

A sign of the roof of a long time of waiting	Waiting time
Low	My time has passed for a long time, O barbarians, for a long time, I have been satisfied, O buyer's eyes.
Medium	It's been a long time since I bought it I haven't seen a buyer I haven't accepted it for a long time.
Hight	In the past, we used to accept a buyer (why is anyone waiting for a buyer).

Considering the status of suppliers and producers, a distributor will experience varying lead times, and in each case, the amount of lost sales will also change. For each level of lead time, we define a corresponding level of lost sales, denoted in this study as

low Ls (low lost sales), medium Ls (medium lost sales), and high Ls (high lost sales). When the lead time is high, the amount of lost sales is also high, and conversely, when the lead time is low, the lost sales are minimal.
Based on the above assumptions, we will illustrate the decision tree in Figure 5 concerning the distributor. In Figure 5, Equation 13 shows the use of the distributor's lost sales estimate when considering the probability of short delivery times.

Relationship 13:

$$Els^{low} = [P(Operational)\times P(Low_{lt}|Operational) \times Low_{Ls}] + [P(Semi\text{-}disrupted) \times P(Low_{Lt}|Semi\text{-}disrupted) \times Low_{Ls}] + [P(Fully\text{-}disrupted) \times P(Low_{Lt}|Semi\text{-}Fully - disrupted) \times Low_{Ls}]$$

Equation 13, abbreviated as D in the figures and equations, can be extended to estimate the lost sales in the medium and high times or regarding the distributor.
Equation 14 predicts the total expected lost sales for the distributor.

Relationship 14:

$$TEL_{sD} = ELS_{low}+ELS_{medium}+ELs_{high}$$

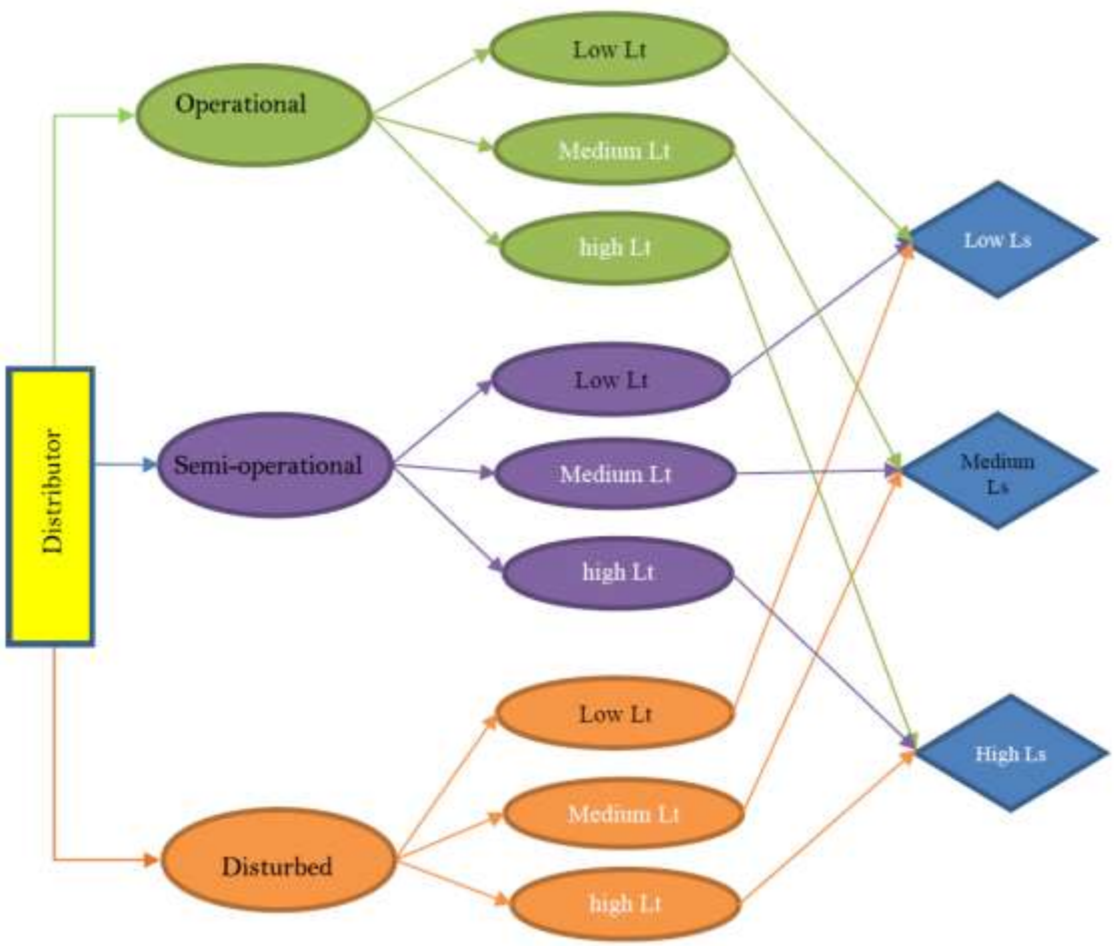

Fig 5. Decision tree including distributor states, waiting time states, and lost sales

To develop a comprehensive measure of the bullwhip effect model and to determine the lost sales for all distributors in the supply chain, we consider a three-tier chain with m suppliers, n manufacturers, and f distributors. Each distributor operates under three conditions: operational, semi-operational, and disrupted, represented by k, along with three levels of lead time or waiting time denoted by one over a time horizon T. Based on the stated concepts and assumptions, the total lost sales for all distributors in the supply chain can be calculated using Relationship 15. This relationship quantitatively illustrates the bullwhip effect caused by distributor disruptions in terms of lead time and lost sales within the supply chain.

Relationship 15:
$TELs_D = \sum_{t=1}^{T}\sum_{r=1}^{f}\sum_{k=1}^{3}\sum_{l=1}^{3} p_{rkt} \times p_{rklt} \times Ls_{rklt}$

5- Results

To analyze the proposed model, we simulate a dynamic Bayesian network for ease of computation and, for example:
In a simple three-layer supply chain for manufacturing voltage amplifiers in three time periods in the case study (Figure 6).
We describe the propagation of disruptions in the chain and examine the bullwhip effect resulting from these disruptions by estimating the lost sales at the distributor level.
Based on the methodology discussed in the previous section, after obtaining the transition matrix using the proposed Markov model and combining it with the Bayesian network, the dynamic characteristics of the supplier disturbances occur in the predicted periods.
To obtain the transition matrix, the status of the first and second suppliers was analyzed over 90 time periods. Given the close similarity in their transfer rates, the recommended Markov model for both providers assumes the transfer matrix to be equivalent over these 90 time periods. However, this is not the case in all supply chains, and depending on geographic location and many other factors, the transition matrix for each supplier may differ.

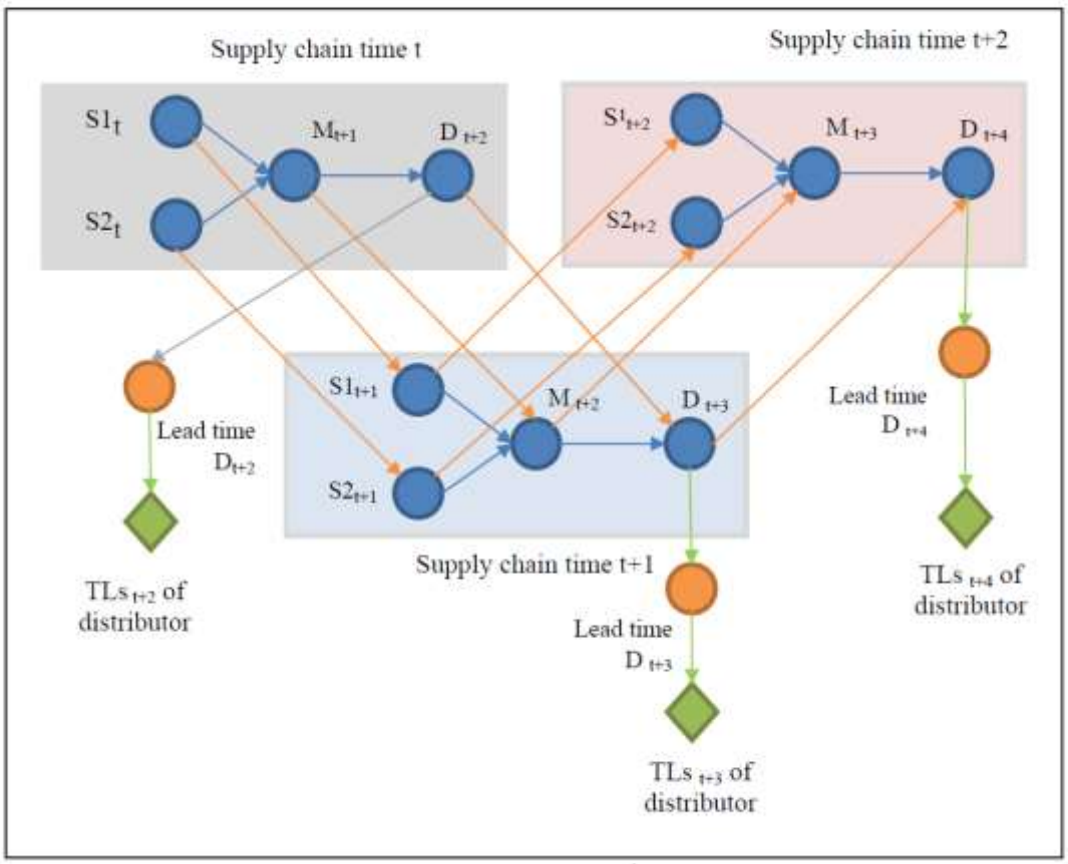

Fig 6: Dynamic Bayesian Network of a Simple Three-Tier Supply Chain with Lead Time and Lost Sales.

The data collection took ninety years. The suppliers are in the following states:

- 73 periods in operational mode.
- 13 periods in semi-operational mode.
- 04 periods in completely disrupted mode.

The transition rates among these states were as follows:
The transition matrix has been calculated based on the following parameters:

- $\beta=1$
- $\mu_2=2$
- $\lambda_3=0$

- γ =5
- μ_3 =8
- λ_1 =3
- λ_2 =6
- α =64

Table 3 presents the results according to Equation 12.

Table 3: Conditional Transition Probability Table (Transition Matrix) for Suppliers in Three States.

T+Δt			
T	Operational	Semi-operational	Disturbed
Operational	0-88	0-08	0-04
Semi-operational	0-62	0-38	0
Disturbed	0-25	0-5	0-25

To examine the effect on risky supply chain paths in addition to the impact of each supplier disruption, we first analyze the distributor's status simultaneously when the production line is active as well as when both suppliers are operational. Then, we will simulate three hypothetical scenarios. In the first scenario, we assume a complete disruption of the second supplier; in the second scenario, we assume a complete disruption of the first supplier; and in the third scenario, we presume that both suppliers are entirely disturbed. We will investigate the effects and propagation of the supplier disruption on the manufacturer and distributor. In this analysis, the conditional probability tables for the manufacturer and distributor, along with the relationship between the lead time for the distributor's goods and the distributor's status, are presented in Tables 4 to 6, as obtained with the help of experts. Based on the examination of the sales data for the distributor over 90 time periods, the average amount of lost sales in this chain is 5,000 units during low lead time, 20,000 units during medium lead time, and 50,000 units during high lead time.

Table 4: Conditional Probability Status of the Manufacturer

Suppliers	Suppliers1	Operational			Semi-operational			Disturbed		
	Suppliers2	O	S	D	O	S	D	O	S	D
Manufacturer	Operational	0-93	0-30	0-35	0-23	0-12	0-05	0-20	0-10	0-01
	Semi-operational	0-06	0-65	0-35	0-70	0-80	0-15	0-40	0-20	0-09
	Disturbed	0-01	0-05	0-30	0-07	0-08	0-80	0-40	0-70	0-90

Table 5: Conditional Probability Stat

Manufacturer	Status	Operational	Semi-operational	Disturbed
Distributor	Operational	0-94	0-2	0-02
	Semi-operational	0-05	0-7	0-08
	Disturbed	0-01	0-1	0-9

Table 6: Probability Table of Lead Time for Goods Based on the Distributor's Operational, Semi-Operational, and Disrupted Status.

Disturbed			Semi-operational			Status		
Long waiting time	Waiting time	Low waiting time	Long waiting time	Waiting time	Low waiting time	Long waiting time	Waiting time	Low waiting time
0-75	0-2	0-05	0-1	0-7	0-2	0-01	0-04	0-95

Calculations for each scenario are performed based on equations 9, 13, 14, and 15 based on the simulation model and the arrangement of data in the decision tree related to the distributor. Figures 7 to 10 show the results. Figure 7 represents the baseline scenario, which shows when the production line is operating normally, both suppliers have an operational probability of 80% and 78% at time t. The simulated bullwhip effect and lost sales for the distributor are displayed. As shown in the figure, according to the obtained transition matrix, the probabilities of both suppliers being operational at time t+2 decrease to 77.25% and 73.76%, respectively. Due to this decrease, the operational status of the distributor changes from 67-53 at time t+2 to 66-73 at time t + 3.

However, the semi-operational and disrupted statuses improved compared to time t+2, and due to this improvement, the distributor's lost sales decreased from 13,671 units to 13,001 units (a 4.9% improvement).
Finally:
During this time, the distributor's total lost sales reached 38987 units. Figure 7 shows the remaining changes.
Considering that the probability status in the active state at time t has been established, on expert opinions, in practice, the distributor in the example supply chain experienced a total lost sales (sales minus demand) of 39,500 units over the three examined periods (t+4, t+3, t+2), which is close to the predicted figure from the model. This result indicates the effectiveness of the model.

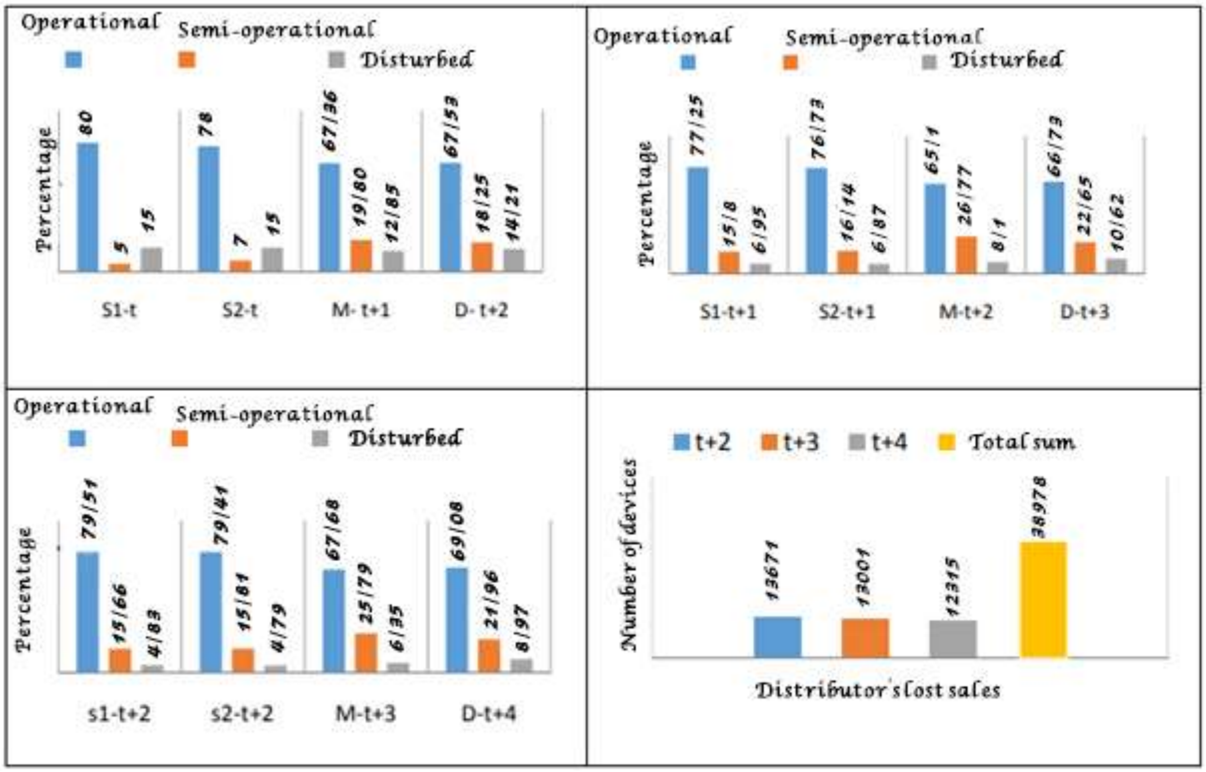

Fig 7. Probability distribution of disruption in three periods of the supply chain and lost sales distribution.
(Both operational suppliers)

In the first scenario:
We assume that the first supplier is in the same state as the base scenario with an operational probability of 80%. Figure 8 shows that the second supplier is disrupted and completely non-operational.
In this scenario:
Given the improvement of about 81% in the distributor's situation at time t+4 compared to t+2 (improvement from an operational probability of 33.55% to an operational likelihood of 61%, the distributor's loss-making sales at time t+4 are about 10,209 units)
In this scenario:
Over a three-period horizon, the total lost sales would be 56,018 units, an increase over the baseline scenario (17,031 units). Therefore, it is clear that if the second supplier is disordered, the ripple effect might spread to the distributor, resulting in an increase of approximately 44% in its lost sales.

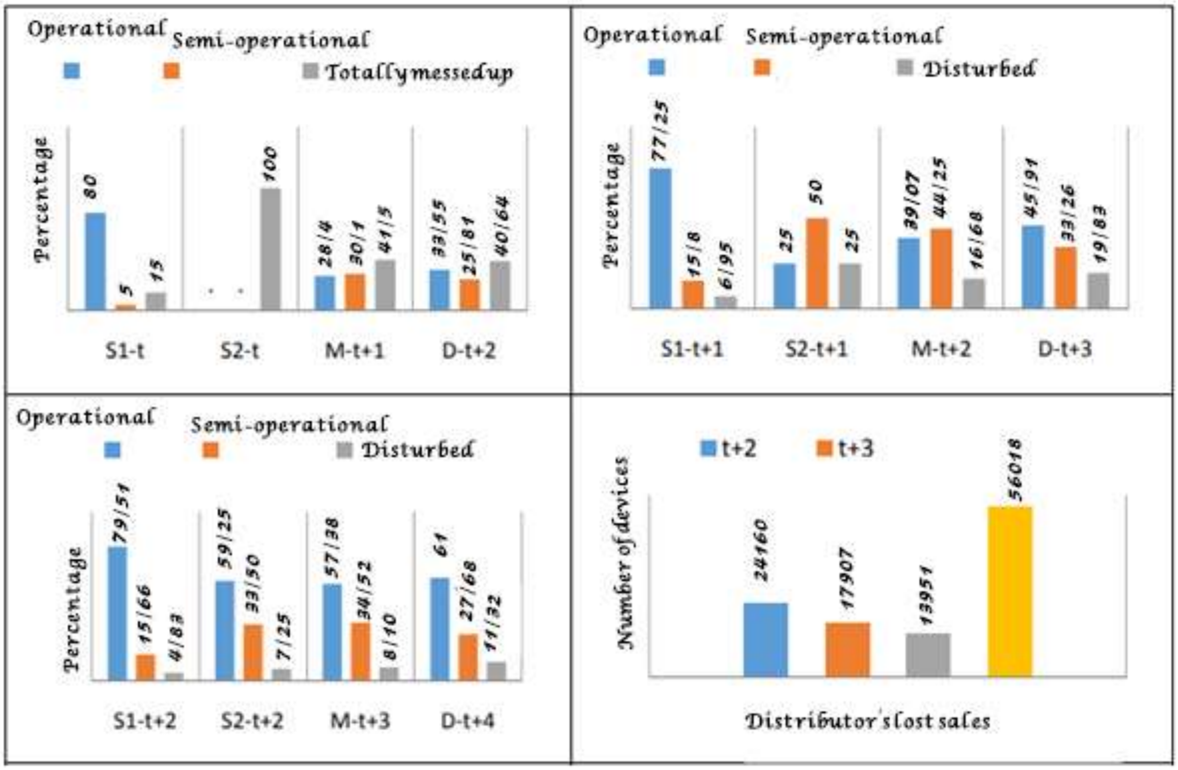

Fig 8. Modeling the ripple effect of complete disruption of the second supplier at time t (Scenario 1).

In the second scenario:

In Figure 9, we show the second supplier in the same state as the base scenario (with a 78% operational probability) and consider the first supplier non-operational.

In this scenario, due to an improvement of approximately 2.56 times in the distributor's status at time t+4 compared to t+2 (with an improvement in operational probability from 23-25% to 59-61%), the lost sales of the distributor have decreased by about 12944 units at time t+4 (approximately a 47% improvement). In addition to observing the ripple effect of disruption in the supply chain by comparing the lost sales of the distributor from period t+4 to t+2, the ripple effect of disruption can also be visible by comparing the total lost sales of the distributor across each time horizon with the subsequent horizon.

In this scenario:

That means an increase of 21,572 units. That is a 55% increase. Compared to the base scenario, there is a rise of 4,541 units compared to the first scenario.

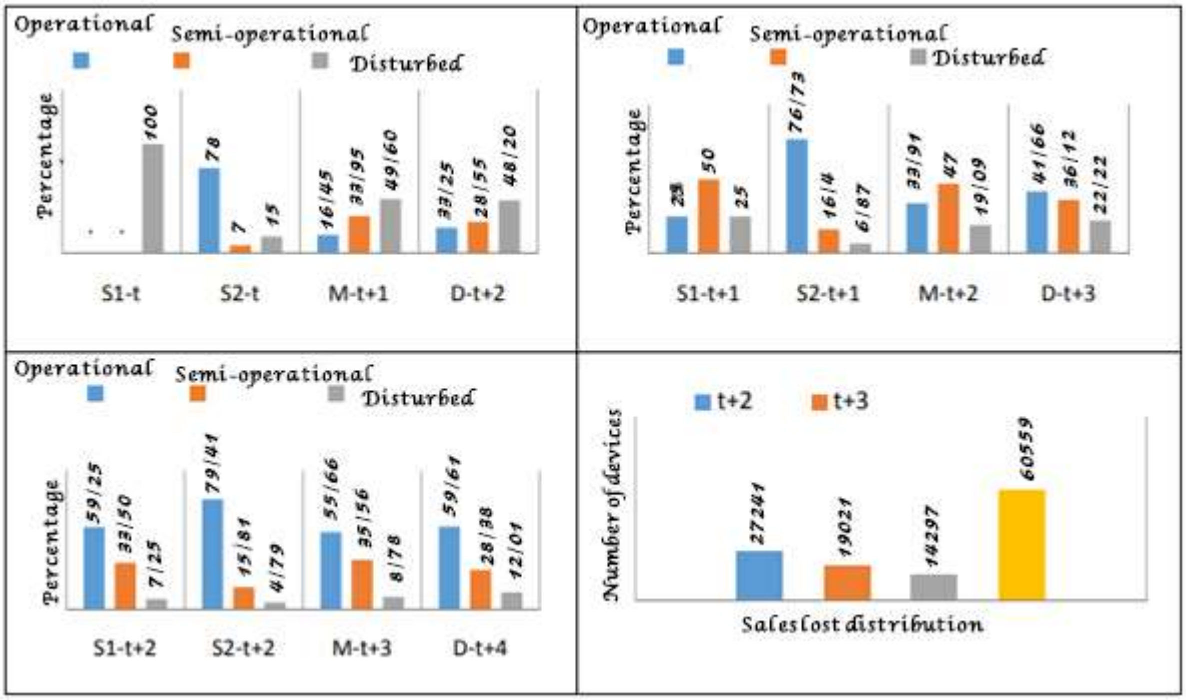

Fig 9. Modeling the ripple effect of complete disruption of the first supplier at time t (Scenario 2).

In the third scenario:

As shown in Figure 10, we consider both suppliers to be completely non-operational. In this scenario, the total lost sales amount to 76,169 units, which is an increase of 37,182 units compared to the base scenario, an increase of 20,151 units compared to the first scenario, and an increase of 15,610 units compared to the second scenario.

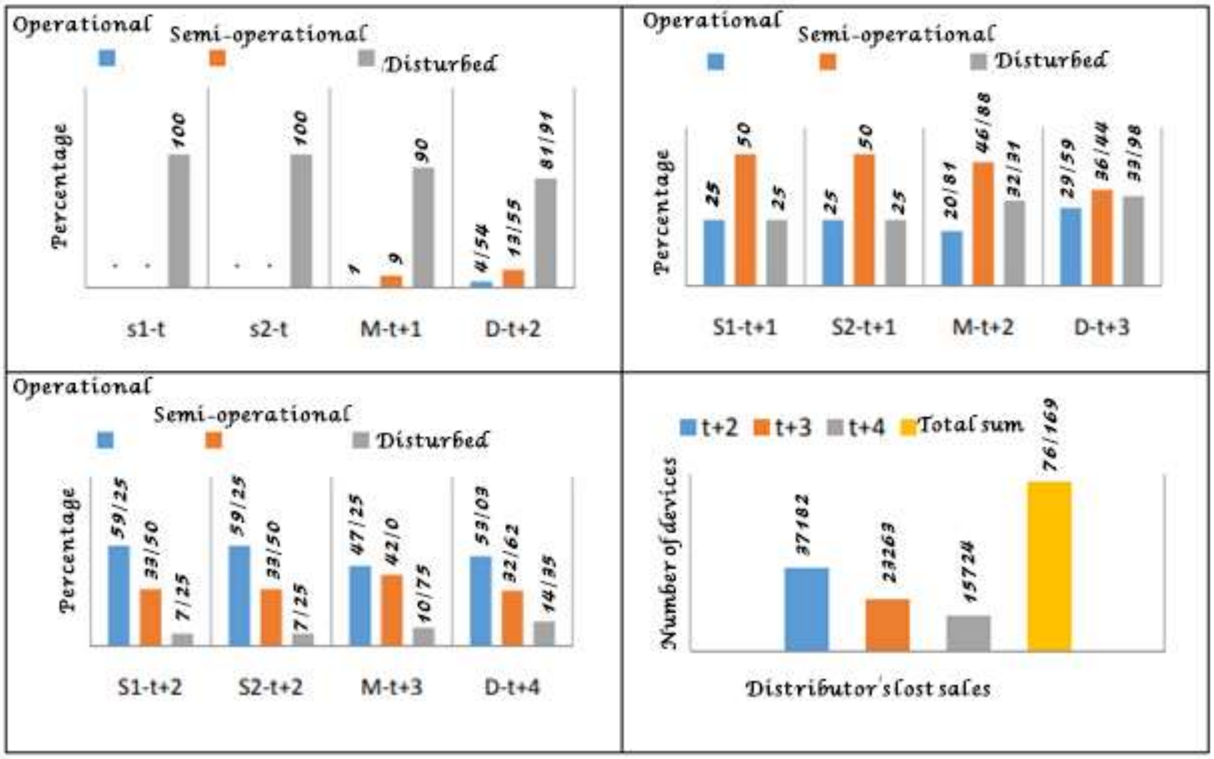

Fig 10. Modeling the ripple effect of complete disruption of both suppliers at time t (Scenario 3).

Figure (11) summarizes the ripple effect caused by supplier disruptions in the defined scenarios, quantitatively represented in terms of lost sales for comparison. This analysis shows how a disruption occurring at a time t upstream in the supply chain, specifically at the supplier, affects downstream in the chain. It allows for testing the chain's path and identifying the unit with the highest impact within the chain. In the examined supply chain, the disruption of the first supplier has had a superior effect on the supply chain. In the event of a disruption in the first supplier, its ripple effect is more significant than that of the second supplier. Therefore, managers can use such analyses to reassess their strategies, including supplier selection, adopt alternative tactics, or modify existing inventory policies.

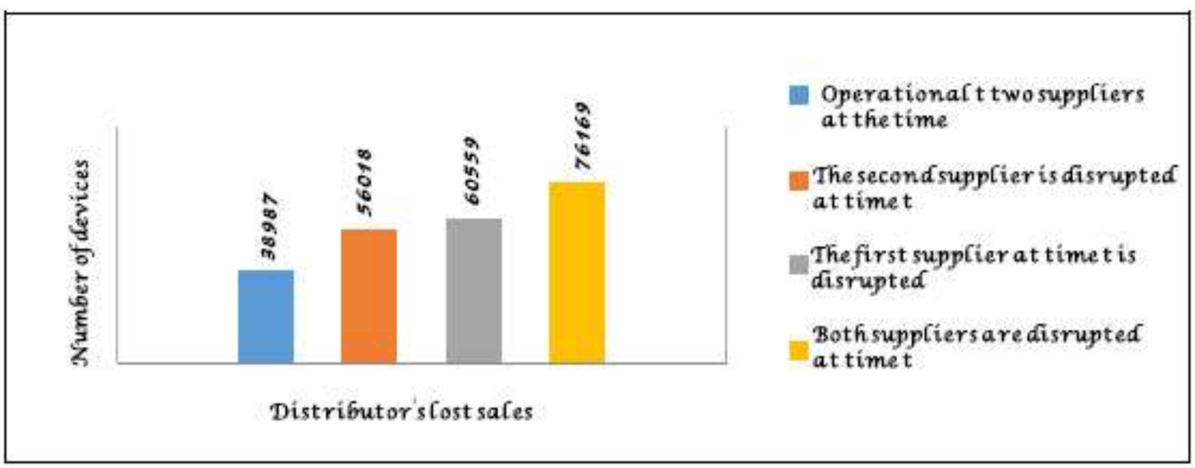

Fig 11. Comparison of the ripple effect of supplier disruptions on the distributor in terms of lost sales.

Analysis of the Role of Supply Chain Units in Lost Sales

We updated the guidelines to understand which unit in the supply chain (supplier, manufacturer, or distributor) has the highest impact on lost sales in the supply chain example. Initially, we assumed both suppliers to be 100% operational at time t, resulting in lost sales of 30,566 units. Given the genuine collected data, the average minimum lost sales over three era periods is 15,000 units, that is to say, a significant distance from the figure of 30,566. It indicates that each manufacturer and the distributor must take action to improve their situation."

Once again, assuming the suppliers are 100% operational, we increased the operational probability of the manufacturer in the conditional probability table (Table 4) from 93% to 100%, resulting in lost sales of 27,951 units. Then, while keeping the two previous changes constant, we changed the operational probability of the distributor in the conditional probability table (Table 5) from 94% to 100%, which resulted in lost sales of 25,204 units.

The above analysis indicates that we have still not approached 15,000 units. Therefore, this time, the suppliers' transition matrix (Table 3) increased the operational probability of the suppliers at time t+1 while they are operational at time t, from 88% to 100%.

It led to a sharp reduction in lost sales, bringing the figure down to 18,150 units, close to 15,000 parts.

The above analysis shows that in this supply chain, the resilience and recovery capacity of the suppliers plays a more significant role in reducing lost sales. Therefore, a policy should be adopted to maintain high supplier capacity in the event of a disruption or to ensure that they recover and reach high capacity as quickly as possible. Manufacturers can also consider alternative suppliers or adopt better inventory policies within the chain. Through the analyses conducted in the previous section and this section, it is possible to examine the supply chain path in terms of disruption hazard and analyze the performance of the supply chain using the presented model, thus making appropriate decisions for adopting the right policies.

The findings of this study clearly show that supplier disruptions have **considerable effects on** the performance of distributors in the supply chain. The 44% increase in lost sales across different scenarios demonstrates the importance of the ripple effect concept. This concept introduces a new framework in supply chain disruption management and helps managers better understand how disruptions spread from suppliers to other departments. Using hybrid models such as Markov chains and Bayesian networks can also help analyze the risks associated with disruptions. The following formula allows us to make accurate predictions of the state of the distributor at time t:

$$P(X_t) = \sum P(X_{t-1}) \cdot P(X_t | X_{t-1})$$

This formula shows the importance of previous states in predicting future states and can help managers design better approaches to risk mitigation**.** The results also emphasize the importance of creating effective strategies for managing disruptions. If a supplier's status changes from completely disrupted to partially disrupted, lost sales are expected to decrease by 30%. This change can lead to the evolution of new frameworks in strategic supply chain management. Overall, these findings can help develop new theories in supply chain management. Analyses suggest creating resilience plans for supply chains to mitigate the effects of disruption and improve performance. The research provides a foundation for future studies on supplier disruptions and increases understanding of supply chain dynamics.

6- Discussion

A-Interpretation of results

The simulation model and dynamic Bayesian network analysis results indicate significant impacts of supplier disruptions on distributors within the supply chain. These analyses show that any interruption at the supplier level can notably affect the performance of distributors. Specifically, the findings from various scenarios demonstrate that a disruption in a supplier can lead to a substantial increase in lost sales. For example, in the first scenario, a disruption in the second supplier resulted in a 44% increase in the distributor's lost sales. It contrasts with Ivanov et al. (2019), who reported a 25% reduction in service levels without a deeper analysis of the effects stemming from the propagation of disruptions within the supply chain. Moreover, in the second scenario, with a disruption in the first supplier, the distributor's lost sales were approximately 55% higher than the baseline scenario, which is significantly greater than the findings of Zhao et al. (2022), who only noted an increase in costs by up to 50%. In the third scenario, where both suppliers were disrupted entirely, the lost sales reached 76,169 units. These results clearly illustrate the compound effects of disruptions and differ markedly from the findings of Hosseini et al.. (2020), who referenced a 20% decrease in demand. While previous research has focused on the overall impacts of disruptions, our study provides a hybrid model combining Markov chains and Bayesian networks, offering a more precise analysis of how disruptions propagate and their effects. It aids managers in developing more effective strategies for supplier selection and inventory management. This study represents a scientific breakthrough in managing disruptions in multi-layer logistics networks. The study represents a scientific breakthrough in managing disruptions in multi-layer logistics networks. Understanding disruption propagation paths and their impacts on supply chain performance represents a significant advance over previous research.

B- Significance and Implications

Research in supply chain management is highly significant and has profound implications for management decisions. This study helps managers design efficient strategies for identifying and managing disruptions, which leads to cost reduction and maintaining supply chain performance. The results of this research can also help create more comprehensive frameworks for managing disruptions in multi-level supply chains and improve coordination and collaboration between chain components. By identifying the propagation paths of disruptions and their impacts, this study can help increase the resilience of supply chains to crises and uncertainties. The information obtained allows managers to make better determinations in supplier selection and inventory management, which helps improve efficiency and reduce risk. Finally, this research can serve as a basis for future research in the field of disruption management and supply chain resilience and help researchers find new methods to improve supply chain performance.

C- Restrictions and Future Research

This study is affected by several limitations that may affect the generalizability of its findings. First, the original model focuses on a specific type of supplier disruption that may not capture all possible scenarios across industries. The data used in the simulations is from a limited time frame. It may ignore long-term trends and changes in supply chain dynamics. In addition, the assumptions made in Markov chain models and Bayesian networks may simplify complex real-world interactions and lead to the neglect of subtle behaviors of supply chain disruptions. Future research is needed to address these limitations and expand the understanding of supplier disruptions in supply chains. Researchers could examine a broader range of disruption types, including disruptions associated with geopolitical factors, technological changes, and natural disasters. Longitudinal studies that analyze the impacts of disruptions over time can provide deeper insights into recovery patterns and long-term effects on supply chain performance. Furthermore, incorporating more sophisticated models that regard dependencies between different supply chain entities can improve the predictability of disruption impacts. Finally, exploring the role of emerging technologies, such as artificial intelligence and blockchain, in mitigating the effects of disruptions may offer innovative solutions to improve the resilience of supply chains.

D- Comparison with previous findings

This study provides a significant advance over previous research on supply chain disruptions. While most studies have examined the overall effects of disruptions, our research focuses on elements of how these disruptions propagate and their specific impacts on distributors. Sindhwani et al. (2023) focus on the capabilities of mitigating the ripple effect in the Indian pharmaceutical distribution network and examine methods for managing disruptions (Sindhwani et al., 2023). In contrast, our study uses a hybrid Markov chain model and Bayesian networks to analyze the ripple effects and identify disruption propagation paths. We show that disruptions can lead to a significant increase in lost sales and also assess the weaknesses of suppliers. This approach helps managers design better risk management strategies and make supplier selection decisions.

Bussieweke et al. (2024) reviewed the ripple effect in supply chains, emphasizing a general analysis of its impacts but paying less attention to the details and quantitative models **connected to** how disruptions propagate (Bussieweke et al., 2024). In contrast, our research focuses on developing a combined Markov chain and Bayesian network model. It provides a detailed analysis of the effects of disruptions on distributors and shows that these disruptions lead to significant increases. We also identify supplier weaknesses and assess specific risks in the supply chain, which helps managers make better decisions about risk management and supplier selection.

Yang & Peng (2023) present supply chain recovery strategies during the COVID-19 pandemic, focusing on product changes and examining supply chain resilience methods (Yang & Peng, 2023). In contrast, our research focuses on the effects of supplier disruptions and how they propagate to distributors. We develop a hybrid Markov chain and Bayesian network model that provides a detailed analysis regarding the impacts of disruptions on lost sales. While Yang & Peng (2023) focus on product changes and recovery strategies, we identify disruption propagation paths and assess supplier vulnerabilities. This approach helps managers make more effective decisions on supplier selection and inventory management and develop better strategies to mitigate the effects of disruptions. Our study has a significant advantage over Yang & Peng (2023) in the analysis and details of how disruptions propagate and their impacts on distributors.

Ali et al. (2021) offer recommendations for strengthening facilities and anticipating backup capacities as pre-disruption measures and emphasize the importance of preparing infrastructure to mitigate the effects of disruptions (Ali et al., 2021). In contrast, our research focuses on a detailed analysis of how disruptions propagate from suppliers to distributors and uses a hybrid Markov chain model and Bayesian networks to assess the effects of these disruptions. We examine the actual impacts of disruptions and their ripple effects on lost sales. Our research also identifies supplier vulnerabilities and assesses specific risks in the supply chain, helping managers design more effective risk management strategies and make decisions about supplier selection and inventory management. While Ali et al. Focusing on preventive measures, our study provides a deeper understanding of how disruptions propagate and their impacts on the supply chain and supplies practical insights for responding to these disruptions.

The study by Feizabadi et al. (2021) addresses the challenges associated with making decisions about supply chain configuration and emphasizes the importance of effective supply chain design (Feizabadi et al., 2021). On the other hand**,** our research analyzes in detail how disruptions propagate from suppliers to distributors and assesses their impact on lost sales. This research helps managers design more effective strategies for risk management and supplier selection, aspects that were not explicitly focused on in the study by Feizabadi et al. This research helps managers design more effective strategies for risk management and supplier selection, aspects that were not explicitly focused on in the study by Feizabadi et al., which addressed the difficulties of decision-making**,** our study offers a more comprehensive analytical approach to understanding the impacts of disruptions and designing effective strategies in the supply chain.

E- Policy Implications

Research on supply chain disruptions and their resilience can have important implications for policymaking at the national and international levels. The first implication is the need to develop supportive policies for small and medium-sized suppliers, as these groups are usually more exposed to the risks of disruptions. Governments can help these suppliers become more resilient to crises by providing financial and training facilities. In addition, policymakers should emphasize building strong infrastructure and diversifying supply sources. The text states that adopting policies to reduce dependence on specific suppliers and enhance supply chain security is significant. Encouraging the utilization of new technologies like artificial intelligence and data analytics will help organizations identify and manage disruptions more efficiently. Finally, international cooperation and information exchange between countries are essential in managing supply chain disruptions. These collaborations will help share best practices and management techniques and strengthen the resilience of global supply chains.

Conclusion

Disruptions are a significant issue for supply chains in today's world. In the past two years, the widespread disruption caused by COVID-19 has been crucial to halting supply chains and delaying customer responses. When a disorder occurs at one point in the supply chain, it probably ripples through to other regions of the supply chain and ultimately affects overall performance.

In this study, we willingly offered a discrete-time Markov model for suppliers facing long-term disruptions with three states: operational, semi-operational, and completely disrupted. We then integrated this model into a Bayesian network to simulate and analyze the ripple effect of disruptions throughout the supply chain. Using a dynamic Bayesian network, we simulated the expansion of upheaval and demonstrated how the supplier, manufacturer, and distributor are affected when a disruption occurs.

The aim of presenting the previously cited model was to quantitatively assess the ripple effect of disruptions in three-tier supply chains, considering both vulnerability and recovery capabilities in suppliers. Given that disruptions in suppliers increase the delivery time of goods or services to customers, and this increase in waiting time leads to reduced sales, we proposed a metric that quantifies the ripple effect of supplier disruptions on the distributor in terms of waiting time and misplaced sales. The proposed ripple effect metric was analyzed using data from a case study.

The findings showed that when a disruption occurs upstream in the supply chain, it propagates downstream and impacts overall performance.

The model in this study can illustrate how disruptions spread and affect performance along the supply chain, revealing confidential menace pathways and the function of each commodity during a disruption. Assessing the supply chain and the effect of disturbances and their propagation will assist managers in prioritizing potential policies and recovery strategies, selecting suppliers, and making informed decisions regarding inventory planning. In this section, based on the results of this investigation and the results obtained from the proposed model, suggestions for future research on the ripple effect of developments are presented. This study used a three-state Markov chain model for suppliers.

To include more cases in long-term future studies, we developed a measure to assess the cascading impact of supplier disruptions on distributors, focusing on delays and revenue loss. It evaluated the cascading effect through various supply chain metrics, including costs associated with missed opportunities. Based on the deconstruction determinations and the results obtained from the proposed model, it has provided suggestions for future research on the wave effect of disturbances. The Markov chain model, with three states for suppliers, is highlighted in the present study and will be used to include more states in future studies. We introduced a metric to evaluate the cascading impact of supplier disruptions on distributors regarding delays and revenue losses. This cascading effect can also be measured using various supply chain performance metrics, such as lost opportunity cost.

Furthermore, the vulnerability of supply chains was analyzed using conditional probability tables and fixed transition rates over a time horizon. However, it is feasible to consider geographic locations and different temporal conditions, allowing for variable conditional probability tables and transition rates for each period and each vendor to explore the wave influence.

This study considers a three-tier supply chain. Future research should examine the effect of disruption propagation in a four-tier supply chain that includes retailers and does not identify variable inventory policies.

The disturbances are affected and presented in a dynamic Bayesian network. Receiving information from experts and data determines the supplier's status. However, it also extracts the impact of disturbance stimuli using a Bayesian network.

Since disruptions may initially originate from the manufacturer or distributor or affect all parts of the supply chain simultaneously, this study can subsequently function to examine the ripple effect of such forms of disruptions.

The new theory presented in this study emphasizes the importance of a more detailed analysis of how disruptions spread and their effects on distributors. Using hybrid models such as Markov chains and Bayesian networks, this research helps managers make better decisions in supplier selection and inventory management. It serves as a basis for future research on supplier disruptions and their effects on supply chains and contributes to a better understanding of supply chain dynamics.

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