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Resilience Modeling of Supply Chain Partners Using Bayesian Networks

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Abstract— **Supply chains are increasingly exposed to disruptions caused by natural disasters, technical failures, and human errors, amplified by globalization and system complexity. These vulnerabilities have underscored the need for resilient supply chain (SC) designs that can withstand disruptions, sustain performance, and recover efficiently. Although prior research has largely examined supply chain resilience (SCR) qualitatively, quantitative models that integrate both proactive and reactive decision-making remain limited. In particular, the causal interdependencies among suppliers, buyers, and transportation nodes are often overlooked. This paper addresses this gap by introducing a Bayesian Network (BN) framework for resilience modeling of supply chain partners. The proposed approach captures conditional dependencies between disruptions and SC entities, enabling decision-makers to evaluate resilience under varying scenarios. By quantifying robustness, recovery capability, and the impact of mitigation strategies, the BN model provides actionable insights for enhancing SCR through data-driven probability assessments.**

Keywords— **Supply chain resilience, Bayesian network, risk analysis**

I. INTRODUCTION

The advent of globalization in the 21st century has brought significant opportunities for supply chain (SC) companies. These include reducing overhead costs, enhancing customer service, optimizing inventory management, and increasing operational efficiency. However, despite these benefits, global supply chains have become increasingly vulnerable to disruptions due to their growing complexity and heightened exposure to external risks. These risks encompass geographic factors such as political instability, economic challenges like price volatility, and natural disasters.

For instance, the 2011 floods in Thailand disrupted global supply chains on an unprecedented scale, impacting nearly 10,000 factories, including major corporations like Honda, Canon, Sony, and Goodyear.

These companies were forced to cut production and suffered substantial revenue losses [1]. Beyond the direct effects on domestic manufacturing, the floods also severely affected overseas manufacturers, who faced raw material shortages due to disrupted transportation and infrastructure systems. Transportation is particularly critical for industries heavily reliant on large supplier networks, such as automotive, electronics, and aviation.

Similarly, the 2011 earthquake and tsunami in Japan caused widespread disruptions across global supply chains, including in the automotive and retail sectors in the UK [2]–[4]. According to [5], Nissan was forced to halt production at its Sunderland plant in the UK for three days due to a shortage of engine parts supplied by a Japanese partner located in the earthquake-affected region. Multi-tier supply chains, such as those in the automotive and aviation industries, are particularly vulnerable to such disruptions. For example, an automaker may have multiple plants worldwide and rely on over 10 tiers of suppliers, involving approximately 1,500 companies per tier spread across more than 5,000 locations globally [1].

Designing resilient supply chains that can recover from disruptions quickly and cost-effectively presents a formidable managerial challenge. The examples of supply chain disruptions discussed above underscore the critical need for resilience. A reliable and resilient supply chain minimizes business operation discontinuity and mitigates the risk of losing market share during disruptions. Moreover, the interdependencies between suppliers and manufacturers highlight the necessity of adopting a holistic approach to supply chain resilience. Disruptions that impact a supplier often propagate downstream, affecting manufacturers and other entities. A central challenge in building resilient supply chains lies in understanding the effects of various proactive and reactive mitigation strategies and efficiently allocating resources both before and after disruptions occur. To minimize the likelihood and impact of disruptions, it is essential to quantify supply chain resilience and evaluate how different mitigation strategies influence overall robustness. This paper seeks to address this challenge by developing Bayesian Network (BN) models capable of quantifying and enhancing the resilience of two-echelon supply chains comprising buyer and supplier entities.

These models evaluate the reliability and resilience of supply chains under both single and multiple correlated disruptions, providing decision-makers with valuable insights into designing and managing resilient supply chains.

II. LITERATURE REVIEW

Different definitions have been proposed by scholars to define Supply Chain Resiliency (SCR). For example, Poins and Koronis defined SCR as the ability to return to its original status under emergency risk environments [6]. Hosseini et al. presented a definition of SCR based on the notion of resilience capacity, defining it as the capability of the SC to utilize absorptive capacity to

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withstand the turbulence of disruption and minimize the consequences by utilizing adaptive and restorative capacity with minimal restoration cost [7]. A comprehensive review of SCR definitions can be found in [7]. Although there is no unique definition for SCR, some commonalities can be observed, such as absorptive capability prior to disruption and restoration capability afterward.

There is growing interest in the literature on SCR, but most existing works examine SCR from a qualitative perspective. For example, many research efforts have identified and discussed enablers of SCR such as information sharing between SC entities, collaboration, excess backup inventory, SC visibility, connectivity, and robustness. Recently, more focus has been placed on the quantitative aspects of SCR. For example, in [8], BN was used to evaluate and select resilient suppliers. Similarly, [9] utilized BN to analyze the resilience capacity of inland waterway ports under different disruption scenarios. In [9], a mixed integer programming model was developed to find optimal demand allocation in the presence of disruption risk. Although resilience was not directly measured, the model incorporated drivers of SCR like backup suppliers and multiple sourcing. A BN-based framework to measure the resilience of a sulfuric acid manufacturer was proposed in [9]. Structural equation modeling was used in [8] to examine dependencies between SC capabilities, risk, and resilience, revealing that tighter integration and greater flexibility enhance resilience. Barriers to SCR were measured using Grey clustering and VIKOR in [9]. A graph-based model developed in [9] measured structural redundancy in terms of disrupted manufacturing plants and lost material capacity.

The SCR of a manufacturer was assessed using control theory in [9], which employed the integral of time absolute error to quantify inventory and shipment rate losses. The interface between SCR and sustainability was explored through discrete-event simulation in [10], focusing on the ripple effects of disruptions. A redundancy network optimization model proposed in [10] integrated sustainable resource use and SCR. Control theory methods were also applied for structural-operational design. An adaptive framework to enhance SC decision-making efficiency, consistency, resiliency, and sustainability was proposed in [11]. The role of ICT in building resilience across six industries was examined in [11]. Lastly, [12] proposed a data-driven decision support system using simulation and machine learning for resilient supplier selection, leveraging smart manufacturing data to predict supplier disruption proneness and SC impact.

III. THEORY OF BAYESIAN NETWORK (BN)

BN is a directed acyclic network topology that consists of set of arcs and nodes, in which each node represents a variable (attribute in this study) and each arc represents the dependency between two variables. Without loss of generality, let's denote a directed acyclic graph by G, where V and E represent set of nodes and arcs respectively. An arc from node X to Y encodes an assumption that there is an influential dependence or a direct causal of X on Y; the node X is called to be parent of Y, and node Y is called to be child of X. Each node has an associated probability table, called conditional probability table (CPT). The CPT of a node Z is the probability distribution of Z given the set of parents of Z. For a node Z without any parents, the CPT can be simply the prior probability distribution of Z.

Let's assume that a BN contains *n* variables . The chain rules of joint probability distribution can be represented as follows:

$$P(X_1, X_2, \dots, X_n) = P(X_1|X_2, X_3, \dots, X_n)P(X_2|X_3, \dots, X_n) \dots P(X_{n-1} \quad (1)$$

The Eq. (1) can be rewritten as shown in Eq. (2).

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i|X_{i+1}, \dots, X_n) \quad (2)$$

Eq. (2) can be further simplified by knowing the parents of each node. For example, if we know that and are the parents of , then the joint probability distribution of , can be substituted with . Now, let's assume that denote the parents of node , the full joint probability distribution of BN can be represented as:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i|Parents\ (X_i)) \quad (3)$$

Let's consider the BN model illustrated in Fig. 1 with 5 nodes. The full joint probability distribution of this BN is as follows:

$$P(X_1, X_2, X_3, X_4, X_5) = P(X_1)P(X_2|X_1)P(X_3)P(X_4|X_2, X_3)P(X_5|X_4) \quad (4)$$

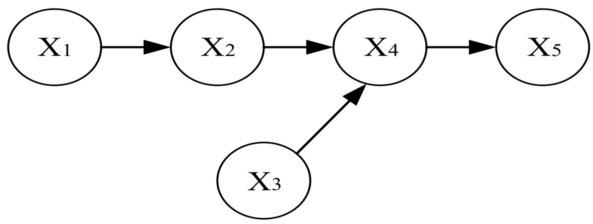

Fig 1. An illustrative example of BN model with 5 nodes.

Marginalization technique can be used to extract the probability of each individual node. For example, the probability of node can be calculated as follows:

$$P(X_2) = \sum_{X_1, X_3, X_4, X_5} P(X_1)P(X_2|X_1)P(X_3)P(X_4|X_2, X_3)P(\quad (5)$$

The global joint probability given in Eq. (5) can be simplified by marginalizing local CPT as below:

$$P(X_2) = \left(\sum_{X_1} P(X_1)P(X_2|X_1) \left(\sum_{X_4} \left(\sum_{X_3} P(X_4|X_2, X_3)P(X_3) \left(\sum_{X_5} P(X_5|X_4) \right) \right) \right) \right)$$

To demonstrate the application of BN, let's consider a simple BN with three nodes: distributor, manufacturer

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1 and manufacturer 2 nodes (parent nodes). As shown in Fig. 2, the distributor node is conditioned on manufacturer 1 and manufacturer 2 nodes whereas each node has two states of operational or disrupted, meaning that the functionality (operational/disrupted states) of distributor depends on functionality of its manufacturers.

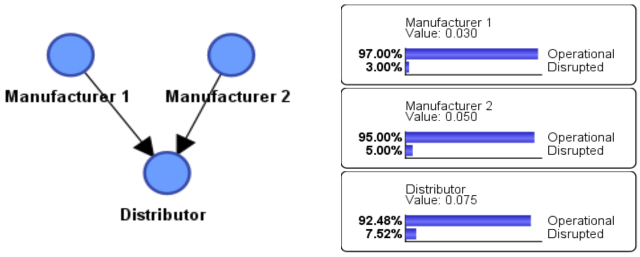

Fig 2. A simple BN with two nodes of manufacturers and a single distributor node and their corresponding distribution probability.

As shown in Fig. 2, the prior disruption probability of manufacturer 1 and manufacturer 2 is 3% and 5% respectively, meaning that there is 3% and 5% chance that manufacturers 1 and 2 fail to supply the finished products to the distributor. The conditional probability table (CPT) of distributor given disruption and operational probabilities of each supplier are represented in Fig. 3. For example, the probability that distributor is being disrupted is 0.75 given that manufacturer 1 and manufacturer 2 are disrupted and operational respectively. The posterior distribution probability of distributor node is calculated based on the conditional probability table (CPT) of distributor and prior probability of two manufacturers as shown in Eq. (7).

TABLE 1. CONDITIONAL PROBABILITY TABLE (CPT) OF DISTRIBUTOR NODE.

Mfg. 1	Operational		Disrupted	
Mfg. 2	Operational	Disrupted	Operational	Disrupted
Distributor Operational	0.98	0.3	0.25	0.01
Distributor Disrupted	0.02	0.7	0.75	0.99

IV. PROPOSED ROBUSTNESS AND RESILIENCE METRICS

In this section, we propose metrics for measuring the robustness and resilience of suppliers and manufacturers with respect to contingency and mitigation strategies. In the supply network, the causal relationship is interpreted as: disruption at x is a direct cause for disruption at y. We assume that the company downstream the supply network will not cause a disruption upstream. This is consistent with typical supply networks, where materials flow from upstream to downstream. It is also assumed that there are no return flows and recycle is not allowed as cycles are not permissible in BNs.

3.1. Metric for measuring robustness of supplier

Robustness of a supplier is defined as the capability of that supplier to withstand against any type of disruption (e.g., local and global disruptions) by pre-positioning sufficient inventory prior disruption occurs. Local disruptions are specific ones that are restricted to each individual supplier. For example, earthquake and fire are considered to be two local disruptions for suppliers who are located in California as those disruptive events are among most natural disasters in California, but hurricane
is considered to be the main natural disaster for the suppliers who are in the south coast of US like New Orleans, LA. The global disruptions are those types of disruptions that globally impact all suppliers regardless of their location and operations such as economic collapse, inflation rate, etc. [12]. Both types of disruptions are considered in the robustness and resilience modeling of suppliers. A different version of this paper is presented at the IMHRC conference [13].

To measure the robustness of supplier, let us define the notations below:

i	Set of suppliers,
j	Set of manufacturers,
g	Set of global disruptive events,
l	Set of local disruptive events,
	Pre-positioned capacity of supplier i
	Quantity of products ordered to supplier i by manufacturer j
	Binary variable which takes value of 1 if local disruption type l occurs on supplier i, and 0 otherwise
	Binary variable which takes value of 1 if local disruption type l occurs on manufacturer j, and 0 otherwise
	Binary variable which takes value of 1 if global disruption type g occurs, and 0 otherwise
	Restoration capacity of supplier i which will be implemented aftermath of disruption
	Restoration capacity of manufacturer j which will be implemented aftermath of disruption
	Demand required by manufacturer j

Let denote the robustness of supplier i and assume that supplier i can be disrupted due to any local and global disruptive event. The can be calculated as follows:

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$$R(s_i) = \sum_{\omega_{il}, \beta_g \in \{0,1\}} P(Z_i > w_{i1} + w_{i2} + \cdots w_{iJ} | \omega_{il}, \beta_g, \forall l \in L_i, \forall g) \times P(\omega_{il} = \psi_{il}, \forall l \in L_i) \times P(\beta_g = \psi_g, \forall g) \quad (8)$$

where, $\psi_{il} = \begin{cases} 1, & \text{if local disruptive event type } l \text{ occurs on supplier } i \\ 0, & \text{otherwise} \end{cases}$

$$\psi_g = \begin{cases} 1, & \text{if global disruptive event type } g \text{ occurs} \\ 0, & \text{otherwise} \end{cases}$$

and is the set of local disruptions impacting supplier i. Let's consider the BN illustrated in Fig. 3(a), in which two suppliers are impacted by both local and global disruptions. In this figure, both suppliers are impacted by global disruption type 1 ($g1$), supplier 1 is impacted by two local disruptions and where the occurrence of is conditioned on the occurrence of . Finally, the second supplier is conditioned on its local disruption and global disruption as well. Let's assume that supplier 1 (must meet the orders that receive from three manufacturers, and represent the quantity of orders that are placed to supplier 1 by manufacturers 1, 2 and 3 respectively. The robustness of the supplier 1, can is calculated by Equation (9):

$$(s_1) = \sum_{\omega_{11}, \omega_{13}, \beta_1 \in \{0,1\}} P(Z_1 > w_{11} + w_{12} + w_{13} | \beta_1 = \psi_1, \omega_{11} = \psi_{11}, \omega_{13} = \psi_{13}) \times P(\beta_1 = \psi_1, \omega_{11} = \psi_{11}, \omega_{13} = \psi_{13})$$

V. SIMULATION RESULTS

In this section, we show how the proposed metrics, discussed in Section IV, can be applied to a two-echelon SC with a set of suppliers and a single manufacturer. To demonstrate the applicability of proposed metrics, let's consider the BN depicted in Fig. 3(b) with three types of nodes; set of suppliers, set of disruptions (global and local), and a single manufacturer. In this figure, the first supplier (is impacted by two local disruptions (hurricane and labor strike) and a global disruption (economic collapse). The second supplier (is conditioned by two local disruptions (earthquake, tsunami) and a global disruption. It is notable that the occurrence of tsunami depends on the occurrence of earthquake. The disruption of Mfg. 1 depends on its local disruption (fire), global disruption (economic collapse), and disruption of suppliers 1 and 2 (.

It should be highlighted that the distribution probability of suppliers and manufacturer is calculated using CPT in a similar way that is demonstrated by Equation (1). For example, supplier 1 is conditioned on three nodes (two local disruptions (hurricane and labor strike) and a global disruption (economic collapse). The CPT of supplier 1 requires entries (three disruption nodes and supplier 1 node). The number of CPT entries could exponentially increase when the number of local and global disruption increases. As such, it is difficult if it is not possible to model the CPT for suppliers and manufacturer with many parent nodes. Instead, we used noisyOR approach that can be used instead of CPT.

The BN capture causal relationships between disruptive events and supply chain (SC) entities, offering a robust method for managing risks under uncertainty. Using conditional probabilities, the model evaluates supplier robustness based on their ability to meet manufacturer demand through normal capacity or pre-positioned inventory (mitigation strategy) under local and global disruptions. Resilience further accounts for restoration capacity (contingency strategy) beyond static buffers. The framework also models interdependencies among disruptive events. Through BN inference, supplier performance is simulated under scenarios such as demand surges, helping SC managers quantify vulnerabilities, anticipate disruption impacts, and strengthen resilience strategies.

Disruption and demand fluctuation modeling

This sub-section aims to analyze the impact of different disruption scenarios on the probability of suppliers to meet the demand of manufacturers. Here, three scenarios are defined. Scenario 1, where the probability of disruption associated with supplier 2 being occurred is changed from 3% in the baseline model (Fig. 3.b) to 65.79%. Under this scenario, the probability that supplier 2 meets the demand of manufacturers 2 and 3 reduces from 96.12% in baseline model to 33.90%. In scenario 2, we are interested to see how the distribution probability of variables should change if supplier 1 aims to fully meet the demand of all manufacturers. As such, we set the probability of "satisfied" state of "satisfied node to 100%, assuming that supplier 1 satisfies the demand of manufacturers by 100% and propagate the impact of this observation by updating the marginal distribution probability of all other unobserved variables. Finally, scenario 3 refers to the case which estimates the likelihood that suppliers 1 and 2 can meet the demand with respect to potential functions on demand variable. In this scenario, we make an observation by assuming that the mean of demand of manufacturer 2 is increased from 38.07 in baseline model (Fig. 4) to 55 (Fig. 5). Under this scenario, the probability of satisfying demand by suppliers 1 and 2 reduce from 93.04% and 96.12% (Fig. 4) to 90.31% and 94.96% (Fig. 5), respectively.

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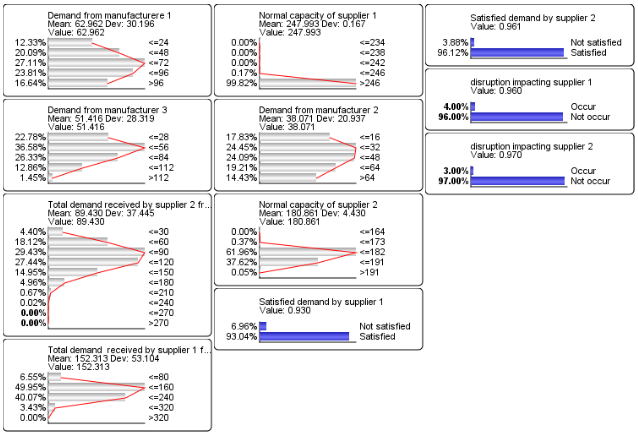

Fig 4. The distribution probability of BN variables shown in Fig. 3(b).

VI. CONCLUSIONS

This paper introduces Bayesian Network (BN)-based metrics to measure the robustness and resilience of suppliers and manufacturers. BNs capture causal relationships between disruptive events and supply chain (SC) entities, making them effective for modeling risks under uncertainty. Supplier robustness is defined by the ability to meet manufacturer demand using normal operational capacity or pre-positioned inventory (mitigation strategy) under local and global disruptions. Resilience extends beyond inventory by incorporating restoration capacity (contingency strategy). The model also captures interdependencies among disruptive events. Using BN inference, we simulate supplier performance under scenarios such as demand surges to evaluate the ability to sustain service levels. The proposed framework enables SC managers to quantify vulnerabilities, assess disruption impacts, and design effective mitigation and contingency strategies.

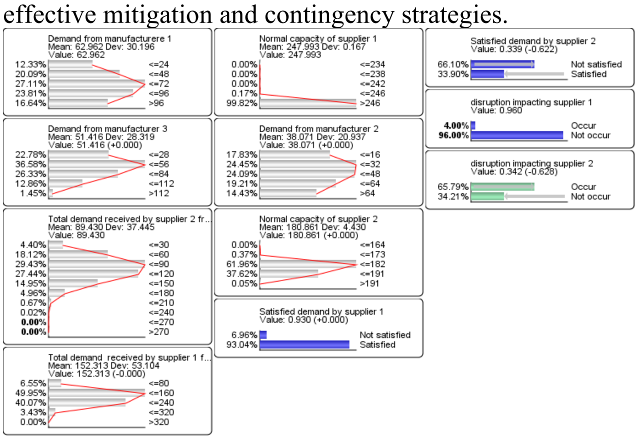

Fig 5. The distribution probability of BN in Fig. 3(b) under scenario 1.

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