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S.I.: DESIGN AND MANAGEMENT OF HUMANITARIAN SUPPLY CHAINS

A new resilience measure for supply networks with the ripple effect considerations: a Bayesian network approach

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Abstract
This is the first study that presents a supply chain (SC) resilience measure with the ripple effect considerations including both disruption and recovery stages. SCs have become more prone to disruptions due to their complexity and strategic outsourcing. While development of resilient SC designs is desirable and indeed critical to withstand the disruptions, exploiting the resilience capabilities to achieve the target performance outcomes through effective recovery is becoming increasingly important. More adversely, resilience assessment in multi-stage SCs is particularly challenged by consideration of disruption propagation and its associated impact known as the ripple effect. We theorize a new measure to quantify the resilience of the original equipment manufacturer (OEM) with a multi-stage assessment of suppliers' proneness to disruptions and the SC exposure to the ripple effect. We examine and test the developed notion of SC resilience as a function of supplier vulnerability and recoverability using a Bayesian network and considering disruption propagation using a real-life case-study in car manufacturing. The findings suggest that our model can be of value for OEMs to identify the resilience level of their most important suppliers based on forming a quadrant plot in terms of supplier importance and resilience. Our approach can be used by managers to identify the disruption profiles in the supply base and associated SC performance degradation due to the ripple effect. Our method explicitly allows to uncover latent, high-risk suppliers to develop recommendations to control the ripple effect. Utilizing the outcomes of this research can support the design of resilient supply networks with a large number of suppliers: critical suppliers with low resilience can be identified and developed.

Keywords Supply chain management · Supply network · Resilient supplier · Resilient supply chain · Ripple effect · Resilience · Bayesian network

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1 Introduction

Due to the rapid globalization of supply chains (SC), greater levels of uncertainty they face, and the evolution of strategic outsourcing, understanding and measuring the impact of disruptions is becoming an increasingly important field of research. Companies that operate at global scale with inherent uncertainty at the structural SC design level have a common question to ask. How do some companies obtain better performance than others under conditions of severe disruptions? The objective of SC management has therefore expanded beyond short term cost savings to long term strategic benefits, such as achieving a high level of resilience considering uncertainty and dynamics the SC confronts.

We consider a SC disruption an unanticipated and unforeseen event that interrupts the normal flow of goods and materials in a supply network (Svensson 2000; Craighead et al. 2007; Elluru et al. 2017; Altay et al. 2018; He et al. 2018). This holds equally true for both industrial and humanitarian SCs (Baharmand et al. 2017; Dubey et al. 2017; Behl and Dutta 2018). SC resilience has been defined in different ways. Brandon-Jones et al. (2014) defined SC resilience as the ability of a system to bounce back to its original state, within an acceptable period of time, after being disrupted. Although there is no unique concrete definition for SC resilience, many definitions highlight the resistance and recovery capability of the SC. The theoretical foundations of SC resilience have been discussed by Ivanov and Sokolov (2013) and Tukamuhabwa et al. (2015), to name a few. In general, SC resilience is usually considered in literature as the operational SC capability to withstand, adapt, and recover from disruptions at a minimal cost to ensure customer demand is fulfilled. More definitions of resilience can be found in Hosseini et al. (2016b, 2019a).

Recent industry examples highlight the need for manufacturing firms to recover quickly after disruption and react to the ripple effect spreading out over the multiple stages in the SC. In May 2017, there was a ripple effect in automotive SC of BMW caused by a supply shortage of steering gears (Arons 2017). The roots of this shortage could be seen at an Italian 2nd tier supplier who was not able to produce certain steering parts due to internal machine breakdowns. This disruption was rippling through the SC whereas the BMW's 1st tier supplier Bosch was not able to deliver the steering gears according to the plan resulting in worldwide production stops at BMW assembly plants.

The Japanese tsunami and earthquake had profound implications on global SCs, inventory levels, profit margins, corporate bottom lines, and broad economic output (ZeroHedge 2011). Many of Toyota's part suppliers were unable to deliver at their expected volume and suffered from significant delays. General Motors had to halt their production due to the shortage of materials from Japanese suppliers. Nissan also suffered considerably because of its high level of dependency on raw material suppliers in the earthquake zone that supplied roughly 12% of its engines (BBC News 2011), forcing Nissan to stop production at its Sunderland, UK plant for several days (Massey 2011; Hosseini and Barker 2016a, b). The impact of the Japanese disruption was not solely limited to the auto industry, but expanded to other industries like electronics as well: Sony suffered from shortages of electronics parts and raw materials, which forced them to suspend production at five plants in central and southern Japan which produced camera lenses, televisions, and other goods (ZeroHedge 2011).

In a more recent example, Meridian Magnesium's main plant caught fire about 1:30 a.m. May 2, 2018 and its roof was destroyed by a series of explosions (Rubbernews 2018). Meridian produces numerous lightweight parts for automotive industry. This fire ripped through a Meridian Magnesium Products of America factory in Eaton Rapids, Mich. The fire brought auto assembly lines around the country to a halt, affecting Ford Motor Co., General

Motors, Fiat Chrysler Automobiles, Mercedes-Benz and BMW. (Automotive News 2018). "BMW is working to develop alternative sources for the parts," the auto maker said in an e-mailed statement to *Automotive News*. "The BMW plant in South Carolina has an inventory of parts on hand but until the supply chain stabilizes there will be some interruptions to X5 and X6 production." (Rubbernews 2018).

These examples highlight that the ripple effect could pose serious risks to OEM (original equipment manufacturer). The difficulty in analyzing the ripple effect that results in a discontinuity of the SC has several reasons. Multi-tier supply networks are particularly exposed to disruptions, because the operations continuity of OEM is highly dependent on the vulnerability of their suppliers and, in turn, the suppliers of their suppliers. In such complex SCs with a large number of suppliers, it is therefore critical for OEMs to identify the level of resilience of their important suppliers.

The ripple effect is one of the challenging issues in assessing the SC resilience in the multi-stage SCs (Ivanov et al. 2014a, b; Dolgui et al. 2018; Ivanov et al. 2019). The ripple effect manifests when a disruption and its associated impact propagate downstream the SC. Recent studies of resilient SCs have focused on assessing the vulnerability of manufacturing firms or the capabilities necessary to manage disruptions (Ellis et al. 2010; Sheffi 2007; Prasad et al. 2017; Bao et al. 2017; Chen et al. 2019; Pavlov et al. 2019). However, in many cases, supply disruption (i.e., stoppage of raw material supply) does not occur at a manufacturing facility, but rather from its supply networks (Kim et al. 2015; Govindan et al. 2016).

A growing body of literature found positive associations that some of the firm's resilience success is attributable to vulnerability and recoverability capabilities of the suppliers (Kull and Talluri 2008; Carbonara and Pellegrino 2017; Wamba et al. 2018; Dubey et al. 2019; Blackhurst et al. 2018; Yoon et al. 2018; Cavalcantea et al. 2019). Researchers and practitioners largely focus on measuring either the supply network vulnerability as a whole (Kim et al. 2015; Blackhurst et al. 2018; Macdonald et al. 2018) or the vulnerability of manufacturing firms and their first tier suppliers, largely in terms of the complexity and number of suppliers (Yoon et al. 2018); literature, though, was mostly focused on isolated supplier and OEM resilience assessments. In addition, recent studies by Hosseini and Barker (2016a, b), Hosseini et al. (2016a, b), Sokolov et al. (2016), Ivanov (2018), Pavlov et al. (2018), Ivanov and Dolgui (2018) point to the practical and theoretical value of inclusion the disruption propagation in the resilience assessment. However, this literature does not specify a comprehensive model for measuring the OEM resilience that incorporates the magnitude of disruption propagation and the supplier resilience as a combination of their vulnerability and recovery capabilities. Recent literature (Blackhurst et al. 2018; Dubey et al. 2018, 2019) concludes that the exploiting the resilience capabilities to achieve the target performance outcomes through effective recovery is desirable and indeed critical to withstand the disruptions. Notwithstanding the importance of the previously developed methods, a more detailed vulnerability analysis can be achieved when the impacts of disruption caused by the suppliers' suppliers (tier 2 and tier 3 suppliers) are quantified, i.e., considering the disruption propagation or ripple effect in the SC (Ivanov et al. 2014a; Dolgui et al. 2018; Scheibe and Blackhurst 2018; Ivanov and Sokolov 2019).

The distinctive feature of our study is an explicit inclusion of the ripple effect in OEM resilience assessment. This is the first study that presents a SC resilience measure with the ripple effect considerations including both disruptions and recovery stages. We contribute to literature by theorizing a new measure of SC resilience with a multi-stage assessment of suppliers' proneness to disruptions and the SC exposure to the ripple effect. We examine and test the developed notion of SC resilience as a function of supplier vulnerability and recoverability using a Bayesian network (BN) and considering disruption propagation. The resilience measure constructed can be used by managers to identify the disruption profiles in the supply base and associated SC performance degradation. The findings further suggest that our model can be of value for OEMs to identify the resilience level of their most important suppliers based on forming a quadrant plot in terms of supplier importance and resilience. Our method explicitly allows to uncover latent, high-risk suppliers to develop recommendations for supplier management. Utilizing the outcomes of this research can support the design of resilient supply networks with a large number of suppliers: critical suppliers with low resilience can be identified and developed.

BN methodology allows assessing resilience with disruption propagation while avoiding two major inconveniences, namely the numerous dependencies among the SC tiers and modeling the impact of rare disruptive events. BNs are capable of describing the causes and effects of system output using a graphical framework that provides rigorous quantifications of risks. BNs are useful for decision making under risk and uncertainty (Fenton and Neil 2013), with risk assessment applications in transportation systems, production systems, and water pollution, among others (Garvey et al. 2015; Tang et al. 2016; Hosseini and Barker 2016a, b; Qazi et al. 2017; Liu et al. 2018).

The rest of this paper is organized as follows. Section 2 contains a literature review covering disruption modeling with a focus on the assessment of SC resilience. The BN approach is briefly explained in Sect. 3. A new metric for quantifying the resilience of supply networks is presented in Sect. 4. The technical aspects of the simulation results are discussed in Sect. 5, while their managerial impacts are outlined in Sect. 6. Section 7 concludes the paper by summarizing the main findings and outlining future research avenues.

2 Literature review

The theoretical foundations of modeling the SC disruptions and resilience build on several perspectives, including behavioral (e.g., Wagner and Neshat 2010; Ellis et al. 2010), qualitative (e.g., Christopher and Peck 2004; Tang 2006; Kovacs and Tatham 2009; Kim et al. 2015), quantitative (e.g., Sheffi and Rice 2005; Craighead et al. 2007; Torabi et al. 2015; Hosseini and Barker 2016a), and simulation (Zhao et al. 2011; Nair and Vidal 2011). Supplier risk exposure has been recognized a new and important dimension in sourcing decisions, supplier selection, assessment and development; particular focus has been directed on uncertain, high-impact-low-frequency events (Kull and Talluri 2008; Narasimhan and Talluri 2009; Talluri et al. 2013; Simchi-Levi et al. 2015; Gao et al. 2019; Yoon et al. 2018). Our study greatly benefited from two research streams, namely the ripple effect assessment and supplier vulnerability analysis.

First and principally, literature extensively dealt with issues of how incorporate the disruption propagation through the supplier network into SC resilience considering the ripple effect (Ivanov et al. 2014a, b; Han and Shin 2016; Dolgui et al. 2018; Ojha et al. 2018; Scheibe and Blackhurst 2018). Different modelling methodologies have been used (Dolgui et al. 2019; Ivanov et al. 2019). Brusset and Teller (2017) studied SC risks and resilience using structural equations modeling. Their work reveals that (1) tighter integration between echelons and increased supplier and manufacturing flexibility can significantly enhance resilience, and (2) the perception of external risk of disruption to SCs can actually decrease how much effort is deployed to achieve resilience. Ivanov (2017) studied the impact of disruption propagation using a discrete-event simulation. Ivanov (2018) investigated disruption propagation in SCs when sustainability factors are taken into account. The result of his study shows that facility fortification and storage facilities have a significant impact on mitigating disruption risks. Ivanov et al. (2016) direct attention to the impact of dynamic recovery policies on mitigating SC disruptions subject to the ripple effect. Pavlov et al. (2018) developed a hybrid fuzzy-probabilistic approach to estimating SC resilience while considering structural dynamics and the ripple effect. The genome method was applied with the objective of including the structural properties of SC design into the assessment of resilience. A comprehensive review of the impact of disruption propagation in the SC can be found in Dolgui et al. (2018). Such a perspective on SC resilience assessment appears to be more relevant in a practical decision-making environment, relative to the inherent problems in estimating the risk-resistance of a firm on the base of vulnerability and recoverability capabilities of its supply network (Hosseini et al. 2016a; Dubey et al. 2018, 2019; Ivanov 2019).

Second theoretical perspective to deciphering supplier disruption risk directs attention to the rich literature on the supplier vulnerability assessment and increasing the SC resilience by disruption mitigation and recovery policies (Hosseini et al. 2019b). A growing body of research was mainly established by utilizing stochastic programming and BN. Chowdhury and Quaddus (2017) used partial least squares based structural equations modeling to analyze the SCR drivers of supply chain resilience. Kamalahmadi and Parast (2017) developed a two-stage mixed integer programming to model supplier selection problem under disruption risk. The authors considered different mitigation strategies such as backup suppliers and pre-positioning inventory and reliability of suppliers. Sahebjamnia et al. (2018) developed a multi-objective mixed-integer probabilistic programming model to assess the resilience of manufacturing in the face of multiple disruptions. The authors argued that the interaction between budget external resources and organizational resilience is critical for achieving the successful recovery strategy.

Käki et al. (2015) used BN approach to model supplier disruptions. They showed that BN method utilization can support strategic decisions such as whether or not to use single or multiple suppliers; which suppliers are more risky than others; and what impacts the complexity of the supply base has on the reliability of the supplier network. Bode and Wagner (2015) studied the effect of complexity and the structure of the upstream SC (supply-side) on the occurrence of disruptions. He showed that several drivers of complexity (i.e., horizontal, vertical, and spatial complexity) increase the frequency of disruptions. Garvey et al. (2015) proposed an analytical framework to investigate the interdependencies of various risks in the SC using BN approach.

Hosseini and Barker (2016a) developed a BN to evaluate suppliers based on primary, green, and resilience criteria, identifying factors that contribute to a supplier's capacity for resilience and the probability that a disruption will occur at a given supplier. Hosseini et al. (2016a) proposed a generic framework that consists of five phases: (1) threat analysis, (2) resilience capacity design, (3) resilience cost evaluation, (4) resilience quantification, and (5) resilience improvement to design resilient SC systems. The authors simulated the impact of several environmental disruptions on the performance of a manufacturing site using the BN method. Ojha et al. (2018) used BN to model the impact of risk on SCs. The authors evaluated the impact of risk propagation in terms of service level, fragility, inventory cost, and lost sales. This finding was further explained in the study by Chen et al. (2017) that demonstrated the impact of indirect effects and propagations of disruption on SC performance using the BN method. The findings in (Pavlov et al. 2018) identify the influence of the network degradation severity and recoverability using hybrid fuzzy-probabilistic approach and genome method of SC resilience assessment.

Third related literature stream is the measuring the resilience. The resilience quantification was evidently positioned in literature for different kind of technical, biological, economic and environmental system, a recent review of which was presented by Hosseini et al. (2016b). In SC domain, stochastic optimization usually bounds the resilience in the range [0, 1] and considers as objective functions that must be maximized in addition to minimizing SC cost as primary objective. For example, Chen and Miller-Hooks (2012) introduced a resilience indicator that measures the post-disruption expected fraction of demand that can be satisfied within pre-determined recovery budgets. Torabi et al. (2015) developed a resilience metric that is a function of absorptive capacity (inventory pre-positioning), adaptive capacity (backup supplier), and restorative capacity (restoration of disrupted supplier). Using BN theory, Ojha et al. (2018) developed a metric to quantify the resilience as a measure of service loss aftermath of disruption. The similarity that can be observed across these two measures, proposed by Torabi et al. (2015) and Ojha et al. (2018), is that resilience is calculated by 1 minus fraction of loss, so both metrics are bounded between 0 and 1. Torabi et al. (2015) measured the loss of supplier capacity, while Ojha et al. (2018) considered the loss of service level. Despite the metrics developed by Torabi et al. (2015) and Ojha et al. (2018) that quantify the resilience of the supply network, some research have not measured SC resilience directly, but rather have tried to measure the drivers of resilience. Käki et al. (2015) developed a BN-based metric that measures the risk deduction in the SCs. The proposed metric is capable of quantifying the impact of disruption propagation throughout multi-tier supply networks. The authors argued that the risk deduction metric can help to identify vulnerable suppliers, and enhance risk mitigation. Hosseini et al. (2019b) quantified SC resilience as a measure of supplier segregation that aims to select a set of geographically dispersed suppliers. While studies have established the salience of vulnerability and recoverability in quantifying the SC resilience, including successful risk mitigation practices, little attention has been directed to their interplay in the settings with disruption propagation.

The research reviewed shows the diversity of knowledge about SC vulnerability and supplier contributions to OEM resilience. However, current literature does not specify a comprehensive model for measuring the ripple effect of a supplier disruption so that resilience of an integrated SC can be assessed. Meanwhile alternative approaches highlight the challenge of the focal company to obtain the data required for measuring SC vulnerability (Wagner and Neshat 2010; Sokolov et al. 2016). In this work, we utilize BN to model the dependencies between supplier disruptions and OEM resilience. We propose metrics to quantify the vulnerability, recoverability, and resilience of OEM in large scale supply networks. The vulnerability metric allows disruption propagation from suppliers to OEM to be quantified, while the recoverability metric accounts for risk reduction when the supplier functions properly with no failure. The resilience of a supplier is then quantified as a ratio of recoverability to vulnerability. Our study conceptualizes and models a unique and comprehensive SC resilience measure that in turn, feeds an explicit quantification of disruption propagation exposure.

3 Theory of Bayesian networks

BNs have been recognized as a powerful tool for dealing with uncertainty, handling risk evaluation, and assisting the decision making process. BNs have been extensively utilized as a decision support tool with a diverse array of applications, such as risk analysis (Song et al. 2013; Smith et al. 2017), reliability engineering (Langseth and Portinale 2007; Marquez et al. 2010), medical diagnosis support (Petousis et al. 2016; Constantinou, et al. 2016), infrastructure resilience (Hosseini and Barker 2016a, b; Ojha et al. 2018; Hosseini et al. 2016a), and decision making (Sierra et al. 2018; Sturlaugson et al. 2017), among others.

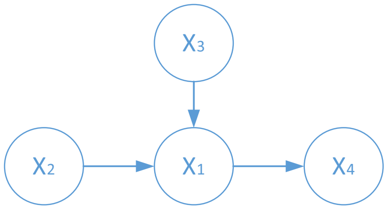

Fig. 1 An illustrative example of BN with four variables

BNs are particularly useful for risk analysis of complex systems for two major reasons: (1) there are numerous dependencies among the components of complex system which can be easily captured by BNs, and (2) BNs are capable of combining historical data and expert knowledge when there is a little historical data available (e.g., modeling the impact of rare disruptive events). Unlike black-box models (e.g., neural networks), there are no hidden variables in the BN model. Furthermore, BNs are capable of modeling both qualitative and quantitative variables. More details about the advantages of BNs can be found in Uusitalo (2007), Boutselis and McNaught (2019), Qazi et al. (2018) and Fenton and Neil (2013).

BNs represent random variables and explicitly model the interdependence between them (Jensen and Nielsen 2007). BNs are graphically represented by directed acyclic graphs (DAGs) with a set of nodes (variables) and set of arcs that express dependency or causal relationship among variables. Different types of variables, including qualitative (low/medium/high), Boolean (yes/no, true/false), or continuous variables, can be encoded in BN models.

To mathematically represent the structure of BN, consider a DAG represented by G, where $G = (V, E)$ and $V = \{X_1, X_2, \ldots, X_n\}$ represents a set of random variables (nodes) and E is a set of arcs. An outgoing arc from X_i to X_j indicates the dependency or causal relationship between these two variables, such that X_i is the parent of X_j, and X_j is the child of X_i. Generally speaking, there are three classes of nodes in BNs: (1) nodes without any child that are called *leaf nodes*, (2) nodes without any parent nodes are called *root nodes*, and finally (3) those nodes with parent and child nodes are called *intermediate nodes*. For example, in Fig. 1, X_2 and X_3 are root nodes, X_4 is the leaf node, and X_1 is intermediate node.

The dependency between a child node and its parent nodes can be quantified by a conditional probability table (CPT). For nodes without any parents, unconditional probabilities or prior probabilities are specified.

The dependencies among variables of a BN can be quantified by conditional probability distributions. Consider a BN with n variables $X_1, X_2, \ldots, X_n$. The general expression for joint probability distribution can be represented as (1):

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

Equation (1) can be rewritten as (2):

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

The joint probability distributions of BN represented in Eq. (2) can be further simplified based on the knowledge of which parent nodes belong to which child node. For example, if node X_1 has exactly two parents, X_2 and X_3, then $P(X_1|X_2, \ldots, X_n)$ can naturally be substituted with $P(X_1|X_2, X_3)$. As such, the joint probability distribution can be simplified to (3).

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n}(X_i|\text{parents}(X_i)) \tag{3}$$

The full joint probability distribution for example illustrated in Fig. 1 can be written as (4):

$$P(X_1, X_2, X_3, X_4) = P(X_2)P(X_3)P(X_1|X_2, X_3)P(X_4|X_1) \tag{4}$$

In this case, we need the conditional probability (from a CPT) for $P(X_1|X_2, X_3)$ and $P(X_4|X_1)$ and the unconditional probability (or prior probability) for $P(X_2)$ and $P(X_3)$. The marginal distribution of each variable (node) can be computed by the marginalization of the joint probability distribution. For example, the formula for marginalization of variable X_2 is given in (5):

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

Note that marginalization is a distribution operation over combinations. This implies that global joint probability can be performed by marginalizing the local node probability. For example, given Fig. 1, $P(X_2)$ can be calculated as (6):

$$P(X_2) = \left(\sum_{X_3} P(X_3)\left(\sum_{X_1} P(X_1|X_2, X_3)P(X_3)\left(\sum_{X_4} P(X_4|X_1)P(X_1)\right)\right)\right) \tag{6}$$

4 Proposed resilience metric

4.1 Modeling a supply network disruption

Under the framework shown in Sect. 3, we now introduce the system to be modelled. Specifically, BNs are acyclic directed networks with a set of nodes and arcs. A material flow supply can be modeled using BN, where each node or variable represents a supplier. The direction of material flow is captured by the direction of the arc. We assume that the rate of return flow is insignificant, so there are no cycles in the network. The relationship $q \rightarrow r$ represents the material flow supplied from supplier q to supplier r. This also means that a disruption at supplier q can cause a disruption at supplier r, as materials flow from supplier q to supplier r. While an upstream supplier can disrupt a downstream supplier (e.g., q disrupting r), it is assumed that a disrupted supplier downstream of SC will not disrupt an upstream supplier.

Represent supplier node i with X_i in a supply network with n suppliers, $i = 1, \ldots, n$ and OEM is denoted by O (this is also the target node of the supply network). Each supplier X_i can be either operational or disrupted. Generally, node X_i, whose parents G are in state g, is in state x with the probability $\mathrm{P}(x|g)$ and $\sum_x \mathrm{P}(x|g) = 1$ for every realization of the states of parent nodes. The conditional probabilities $\mathrm{P}(x|g)$ are called risk parameters. Assume that each node has two binary states (*True* or *False*). Therefore, there are 2^n risk parameters at a node with n parents. It should be noted that *True* represents disrupted state, while *False* represents operational states.

Consider a simple BN model consisting of OEM (node O) and two supplier nodes (X_1, X_2) as represented in Fig. 2. Node O is conditioned on supplier nodes X_1 and X_2, which means

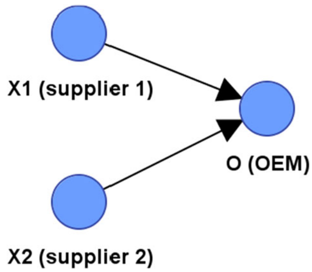

Fig. 2 A simple BN with two suppliers and one OEM

Table 1 Conditional probability table (CPT) of OEM disruption

Supplier 1 (X_1)	Operational		Disrupted	
Supplier 2 (X_2)	Operational	Disrupted	Operational	Disrupted
OEM disrupted	0.01	0.08	0.12	0.21
OEM operational	0.99	0.92	0.88	0.79

that disruption of either supplier can cause the disruption of the OEM. The prior probability of each supplier is assumed to be 3%, suggesting each supplier has a 3% likelihood of failing to supply the OEM. Disruption of a supplier induces disruption at the OEM with a specific probability. Table 1 lists the conditional probabilities of disruption at the OEM due to the i-supplier disruption.

According to Table 1, the probability that the OEM is disrupted if supplier 1 is disrupted and supplier 2 is operational is 0.12. This probability changes to 0.21 when both suppliers are disrupted.

The prior and joint distribution probabilities at supplier and the OEM are represented in Fig. 3. The marginal probability of an OEM disruption is 1.54%, calculated from the conditional probabilities illustrated in Table 1 and based on Bayes' theorem from Eq. (7).

$$
\begin{aligned}
P(\text{OEM disrupted}) = & \sum_{X_1, X_2} P(\text{Supplier disrupted } | X_1, X_2) \times P(X_1) \times P(X_2) \\
= & \, P(\text{OEM disrupted}|X_1 = \text{disrupted}, X_2 = \text{disrupted}) \\
& \times P(X_1 = \text{disrupted}) \times P(X_2 = \text{disrupted}) \\
& + P(\text{OEM disrupted}|X_1 = \text{disrupted}, X_2 = \text{operational}) \\
& \times P(X_1 = \text{disrupted}) \times P(X_2 = \text{operational}) \\
& + P(\text{OEM disrupted}|X_1 = \text{operational}, X_2 = \text{disrupted}) \\
& \times P(X_1 = \text{operational}) \times P(X_2 = \text{disrupted}) \\
& + P(\text{OEM disrupted}|X_1 = \text{operational}, X_2 = \text{operational}) \\
& \times P(X_1 = \text{operational}) \times P(X_2 = \text{operational}) \\
= & \, (0.21 \times 0.03 \times 0.03) + (0.12 \times 0.03 \times 0.97) + (0.08 \times 0.97 \times 0.03) \\
& + (0.01 \times 0.97 \times 0.97) = 1.54\%
\end{aligned}
\tag{7}
$$

Note that the CPT of an OEM disruption as represented in Table 1 requires $2^3 = 8$ risk parameters, as there are $n = 3$ nodes, where each node has two binary states (True or Disrupted) vs. (False or Operational). In practice, constructing a CPT from an OEM disruption can be challenging because the OEM may receive materials from many suppliers, meaning

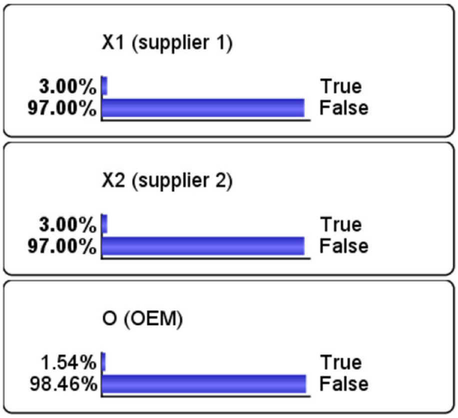

Fig. 3 Prior and joint disruption probabilities of suppliers and the OEM calculated using CPT

that the disruption of an OEM is conditioned on the disruption of many suppliers. To deal with this issue, we utilize the noisy-OR model to build the causal relationship between disruption at parent and child nodes in large supply networks. The main advantages of utilizing noisy-OR model include: (1) it significantly reduces the computational efforts in large supply networks, particularly when OEM is conditional based on dozens of suppliers, and (2) the number of required elicitation probabilities is much lower relative to a BN built using a CPT.

Suppose that there are n suppliers, $X_1, X_2, \ldots, X_n$, that affect the status of O (OEM). Assume that there is a probability associated with O being disrupted when one and only one X_i (supplier i) is disrupted and all suppliers other than X_i are operational. The noisy-OR model for the O node can be expressed as shown in (8):

$$NoisyOR\Big(X_1, v_{O|X_1}, X_2, v_{O|X_2}, \ldots, \bar{X}_i, v_{O|\bar{X}_i}, \ldots, X_n, v_{O|X_n}, \theta_O\Big) \tag{8}$$

where each i, $v_{O|X_i} = P(O = \text{disrupted}|X_i = \text{disrupted}, X_j = \text{operational for each} j \neq i)$ is the conditional probability of the OEM being disrupted if, and only if, the supplier is alone disrupted and other suppliers are operational. There is a leak variable θ_O that represents the probability that the OEM is disrupted when all suppliers are operational. The leak variable is taken into account because the disruption of the OEM does not depend only on supplier disruption, but also on several other disruptions that may occur at manufacturing sites (e.g., machine failures, labor strikes, economic collapse of manufacturer, natural disaster). The leak variable is defined as (9):

$$\theta_O = P(O = \text{disrupted}|X_1 = \text{operational}, X_2 = \text{operational}, \ldots, X_n = \text{operational}) \tag{9}$$

By applying the noisy-OR model, we assume that each supplier operates independently of others in terms of their effects. To understand how the noisy-OR model is utilized, consider an example of an OEM with two suppliers 1 and 2 that feed materials to the OEM. The conditional probability of a disruption at the OEM due to disruption at supplier i, $\forall i = 1, 2$, is represented by $v_{O|\bar{X}_i}$. The leak probability of OEM (node O) is θ_O. The prior probability of the disruption at supplier i is denoted by η_i, and the marginal distribution probability of the O node is represented by F_O. Assume that $v_{O|\bar{X}_1} = 40\%$, $v_{O|\bar{X}_2} = 55\%$, $\theta_O = 5\%$, $\eta_1 = 3\%$, and $\eta_2 = 4\%$. The marginal probability of an OEM disruption is calculated in Table 2.

Table 2 Calculating the marginal distribution probability of OEM, F_O using noisy-OR technique

States g	$P(O\|g)$	$P(g)$
$g_1 = \{X_1, X_2\}$	$\theta_O = 0.05$	$(1-\eta_1)(1-\eta_2) = 0.93$
$g_2 = \{X_1, \bar{X}_2\}$	$1-(1-\theta_O)\left(1-v_{O\|\bar{X}_2}\right) = 0.573$	$(1-\eta_1)\eta_2 = 0.039$
$g_3 = \{\bar{X}_1, X_2\}$	$1-(1-\theta_O)\left(1-v_{O\|\bar{X}_1}\right) = 0.43$	$\eta_1(1-\eta_2) = 0.029$
$g_4 = \{\bar{X}_1, \bar{X}_2\}$	$1-(1-\theta_O)\left(1-v_{O\|\bar{X}_1}\right)\left(1-v_{O\|\bar{X}_2}\right) = 0.74$	$\eta_1\eta_2 = 0.001$
	$F_O = \sum_g P(O\|g) \times P(g) = 0.082$, $F_O = 8.20\%$	

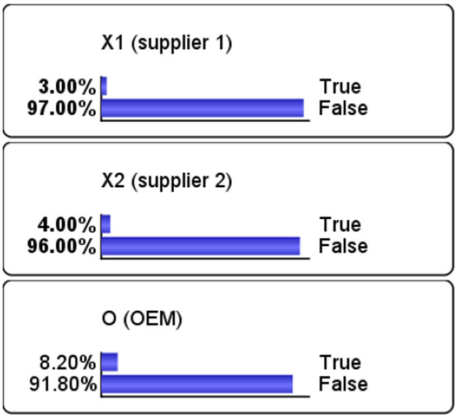

Fig. 4 Prior probabilities of two suppliers and marginal distribution probabilities of OEM calculated using noisy-OR model

In Table 2, there are four states, $g_1, \ldots, g_4$. In state g_1, both suppliers are operational, (X_1, X_2). In the second state, the first supplier is fully operational (X_1 is 100% in the False state), but the second is fully disrupted ($\bar{X}_2$ is 100% in the True state). In the third state, supplier 1 is fully disrupted ($\bar{X}_1$), and supplier 2 is operational (X_2). Finally, in the fourth state, both suppliers are disrupted, $(\bar{X}_1, \bar{X}_2)$. The probabilities of two suppliers and an OEM modeled using noisy-OR model is illustrated in Fig. 4. As shown in Fig. 4 and Table 2, the probability F_O of OEM disruption is 8.2%.

4.2 Proposed metric for quantifying resilience

Henry and Ramirez-Marquez (2012) introduced a metric that quantifies the resilience of a system, represented by Я(t), as a ratio of recovery to loss of that system at time t given disruptive event e^j. The performance of system at time t is denoted by $\varphi(t)$ in Fig. 5. Three transitions states have been used in this model: (1) steady state, where the system performs normally at time t_0 prior to the disruption occurrence, (2) the vulnerability state where the system is affected by disruptive event type j, e_j, that occurs at time t_e, and performance gradually reduces to $\varphi(t_d)$ at time t_d, and (3) the recoverability state, where the recovery activity initiates at time t_s and the service function of the system increases from $\varphi(t_d)$ to $\varphi\left(t_f\right)$ at time t_f. Resilience is measured as the ratio of recovery to loss in terms of service

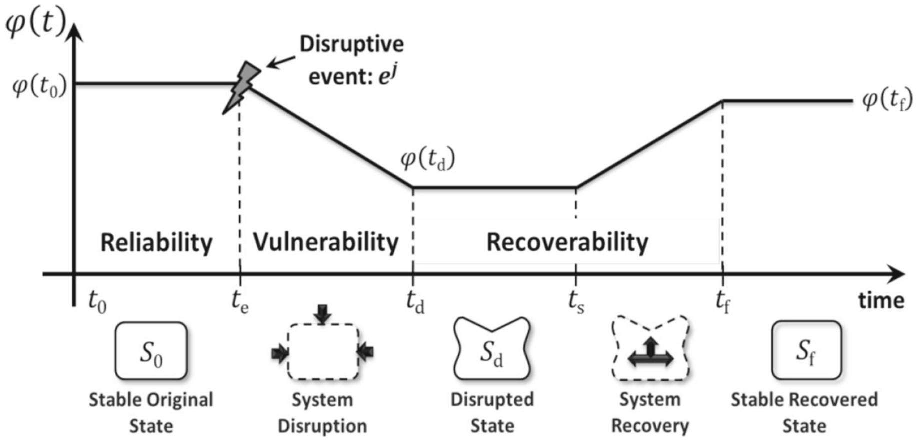

Fig. 5 System performance and state transition to describe system resilience [Adapted from Henry and Ramirez-Marquez (2012)]

function as represented in Eq. (10).

$$\text{Я}\left(t\middle|e^j\right) = \frac{\varphi\left(t_f\middle|e^j\right) - \varphi(t_d|e^j)}{\varphi(t_0) - \varphi(t_d|e^j)} \tag{10}$$

The resilience measure can be less than 100% if the recovered level is less than loss level, equal to 100% if the recovered level is exactly equal to the loss level, and greater than 100% if the recovered level is greater than the loss level.

The resilience of OEM in this paper is measured as a function of its vulnerability and recoverability when its supplier fails to supply because of a disruption. Let $\text{Я}_{O|X_i}$ denote the resilience of the OEM corresponding with supplier X_i, and let $V_{O|\bar{X}_i}$ and $\mathcal{R}_{O|X_i}$ represent the vulnerability and recoverability indices, respectively, of the OEM given that supplier X_i is disrupted. $\text{Я}_{O|X_i}$ is then expressed as a function of $V_{O|\bar{X}_i}$ and $\mathcal{R}_{O|X_i}$, $\text{Я}_{O|X_i} = f(V_{O|\bar{X}_i}, \mathcal{R}_{O|X_i})$.

The vulnerability index, $V_{O|\bar{X}_i}$, measures the percentage that disruption risk at the OEM is increased (marginal disruption probability) when supplier i $\left(\bar{X}_i\right)$ is disrupted, that is, $F_O\left(\bar{X}_i\right)$ compared with the baseline case, F_O. To calculate $F_O\left(\bar{X}_i\right)$, we enter evidence describing supplier i, and set its state to be *True*. This means that we make an observation about supplier i when it is disrupted and update the marginal probability of OEM through propagation (11).

$$V_{O|\bar{X}_i} = \left(F_O\left(\bar{X}_i\right) - F_O\right) \tag{11}$$

The recoverability index $\mathcal{R}_{O|X_i}$ measures the decrease in disruption risk (marginal disruption probability) when supplier i is fully operational. To calculate $\mathcal{R}_{O|X_i}$, the state of supplier i is changed to 100% *False*, and the impact is propagated BN to determine the disruption risk of the OEM. In essence, the recoverability index quantifies the effect on the disruption risk at the OEM when supplier i is fully operational. The recoverability index is calculated as shown in (12):

$$\mathcal{R}_{O|X_i} = (F_O - F_O(X_i)) \tag{12}$$

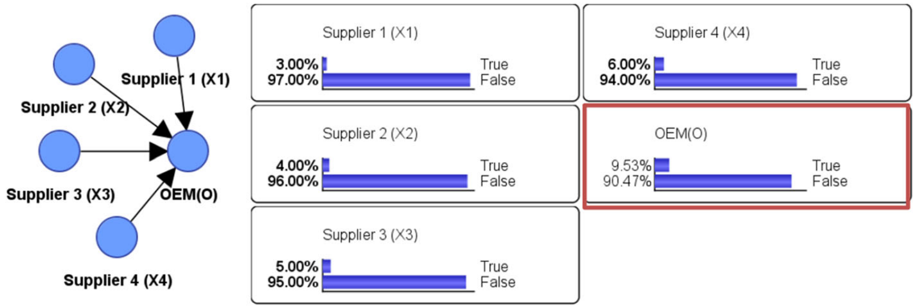

Fig. 6 BN model, prior probabilities of four suppliers and marginal disruption probability of OEM

The resilience value of the OEM corresponding with supplier i is calculated as the ratio of the recoverability and vulnerability indices (13):

$$Я_{O|X_i} = \frac{\mathcal{R}_{O|X_i}}{V_{O|\bar{X}_i}} = \frac{(F_O - F_O(X_i))}{(F_O(\bar{X}_i) - F_O)} \tag{13}$$

To understand how the resilience index is calculated, consider an OEM that is conditioned on four suppliers (X_1, X_2, X_3, X_4). The prior disruption probabilities of the four suppliers are $\eta_1 = 3\%$, $\eta_2 = 4\%$, $\eta_3 = 5\%$, and $\eta_4 = 6\%$, respectively. The disruption probabilities of the OEM given disrupted suppliers are $V_{O|\bar{X}_1} = 31.04\%$, $V_{O|\bar{X}_2} = 35.3\%$, $V_{O|\bar{X}_3} = 39.56\%$, and $V_{O|\bar{X}_4} = 43.83\%$, respectively. The probability of the leak variable associated with OEM is $\theta_O = 2\%$. The disruption risk or marginal disruption probability of the OEM is then $F_O = 9.53\%$, as illustrated in the baseline BN model in Fig. 6. To calculate how much the disruption risk probability of the OEM increases if supplier i is disrupted, we set the value of each supplier to *True* (True state = 100%) and propagate the impact of this observation throughout the BN to measure the impact of this observation on the OEM's risk of disruption. For example, Fig. 8a shows that the disruption risk of the OEM is $F_O(\bar{X}_1) = 40.57\%$ when we have evidence that supplier 1 is fully disrupted. $V_{O|\bar{X}_1}$ is calculated as the difference between F_O and $F_O(\bar{X}_1)$ as calculated in Table 3. The vulnerability index for supplier 1 is 31.04%, which means that the disruption risk of the OEM increases by 31.04% when supplier 1 is disrupted or that the vulnerability of the OEM with respect to supplier 1 is 31.04%. For suppliers 2, 3, and 4, the vulnerability indices are 35.3%, 39.56%, and 43.83%, respectively.

A simple comparison between these four suppliers indicates that $V_{O|\bar{X}_4} > V_{O|\bar{X}_3} > V_{O|\bar{X}_2} > V_{O|\bar{X}_1}$, suggesting that a disruption at supplier 4 increases OEM's risk of disruption. As such, supplier 4 plays a key role in determining the OEM's level of disruption risk. The vulnerability index value can be obtained by performing inference from cause (supplier i) to effect (OEM) by setting evidence that supplier i is 100% disrupted (True state) and measuring the resulting impact of this observation on the posterior distribution probability of the OEM. Considering the illustrative example of the BN model in Fig. 6, the probability of the OEM being disrupted under normal conditions is $F_O = 9.53\%$. This probability can increase to $F_O(\bar{X}_1) = 40.57\%$, as shown in Fig. 8a, when supplier 1 is fully disrupted. Figures 8a-d represent the impact of the four suppliers' observational inference on the OEM for the BN model given in Fig. 6.

A vulnerability index comparison across the four suppliers highlights the importance of reducing the probability of disruption at supplier 4 by analyzing the threats that can lead

Table 3 The calculations of vulnerability, recovery, and resilience index of BN model given in Fig. 6

Supplier i	Vulnerability index ($V_{O\|\bar{X}_i}$)	Recoverability index ($\mathcal{R}_{O\|X_i}$)	Resilience index $\text{Я}_{O\|X_i}$
Supplier 1	$F_O(\bar{X}_1) - F_O = 40.57\% - 9.53\% = 31.04\%$	$F_O - F_O(X_1) = 9.53\% - 8.57\% = 0.96\%$	$\text{Я}_{O\|X_1} = \frac{\mathcal{R}_{O\|X_1}}{V_{O\|\bar{X}_1}} = 0.031\%$
Supplier 2	$F_O(\bar{X}_2) - F_O = 44.83\% - 9.53\% = 35.3\%$	$F_O - F_O(X_2) = 9.53\% - 8.05\% = 1.48\%$	$\text{Я}_{O\|X_2} = \frac{\mathcal{R}_{O\|X_2}}{V_{O\|\bar{X}_2}} = 0.042\%$
Supplier 3	$F_O(\bar{X}_3) - F_O = 49.09\% - 9.53\% = 39.56\%$	$F_O - F_O(X_3) = 9.53\% - 7.44\% = 2.09\%$	$\text{Я}_{O\|X_3} = \frac{\mathcal{R}_{O\|X_3}}{V_{O\|\bar{X}_3}} = 0.053\%$
Supplier 4	$F_O(\bar{X}_4) - F_O = 53.36\% - 9.53\% = 43.83\%$	$F_O - F_O(X_4) = 9.53\% - 6.73\% = 2.8\%$	$\text{Я}_{O\|X_4} = \frac{\mathcal{R}_{O\|X_4}}{V_{O\|\bar{X}_4}} = 0.064\%$

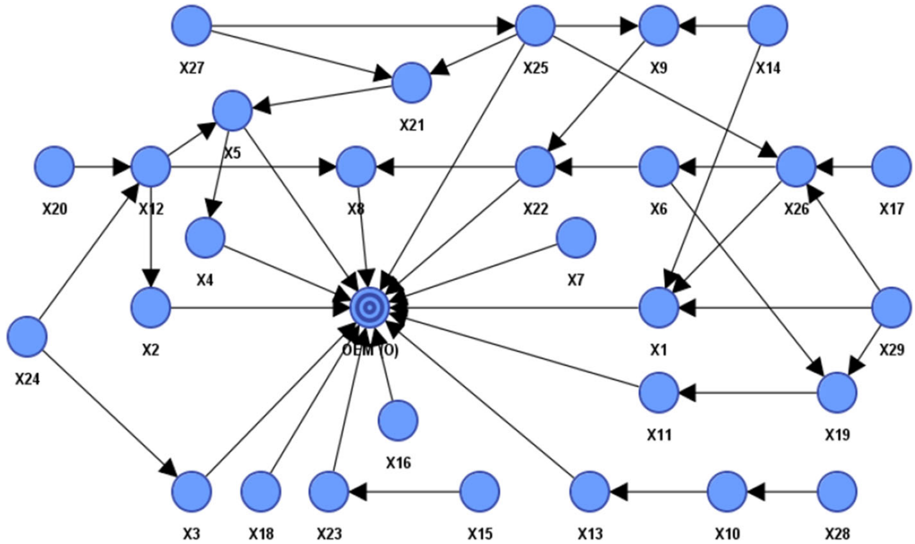

Fig. 7 The BN model of center console supply network of Tiba automobile

to its disruption and developing a pre-disaster strategy (e.g., extra inventory prepositioning, fortifying the physical location of supplier) and post-disaster resilience strategies (e.g., contracting with backup suppliers).

The recoverability of the OEM with respect to each supplier is calculated using Eq. (12). To calculate $F_O(X_i)$, we set the state of each supplier i to their False states by assuming that supplier i is 100% operational and propagate this impact to the risk of disruption at the OEM. The recoverability index of the OEM with respect to each supplier i is calculated in Table 3. Finally, the resilience of the OEM with respect to each supplier i is calculated using Eq. (13).

5 Experimental results

This section introduces a simple case to exemplify the scenarios under which our methodology would be deployed. The application of the proposed metrics is illustrated with an example from the supply network for the center console component part of the Tiba sedan produced by SAIPA, an Iranian automobile manufacturer. Auto supply networks can be very large since OEMs can have somewhere between 50 and 500 suppliers: analyzing multi-tier supply networks with a large number of suppliers and a causal relationship between suppliers can be a difficult task. We utilize the noisy-OR formulation to lessen the computational burden of analyzing a BN developed for the 29 suppliers of this OEM supply network, as illustrated in Fig. 7. The disruption probability of the BN model is extracted from historical data and expert knowledge, as represented in Fig. 9. According to Fig. 9, the risk of disruption at the OEM is $F_O = 8.04\%$ (Figs. 8, 9).

The resilience of the OEM with respect to each supplier is illustrated in Fig. 10. The numerical values show that suppliers 28 and 4 have the highest and least resilience, respectively. Supplier 11 is the most resilient supplier among first tier suppliers (those with direct links to the OEM in Fig. 7). Figure 11 illustrates the vulnerability and recoverability impact of each supplier on the OEM. The result of the vulnerability analysis indicates that a disruption

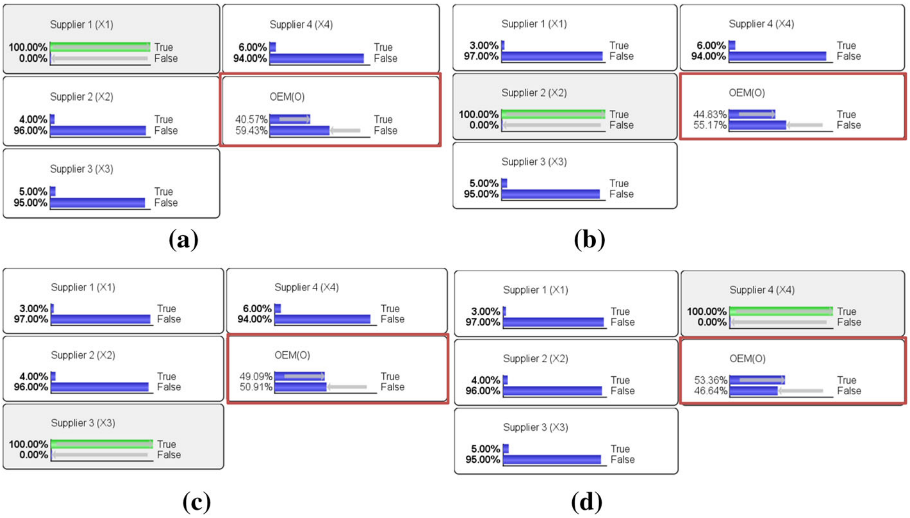

Fig. 8 **a**–**d** Evidential reasoning of suppliers' disruption for calculating $F_O(\bar{X}_i)$

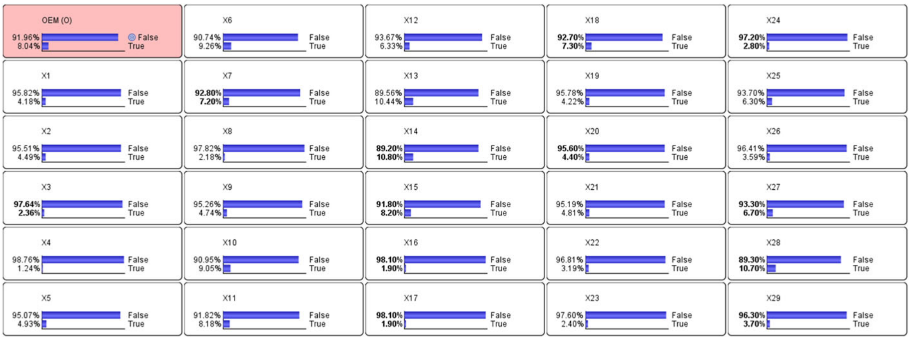

Fig. 9 Distribution probability of suppliers and OEM for center console supply network of Tiba automobile

to supplier 2 has the highest impact on the risk of disruption to the OEM, while the OEM is less sensitive to disruption at suppliers 28, 17, and 10, respectively.

5.1 Sensitivity analysis

A useful means for examining the validity of an expert-built model is to perform sensitivity analysis, whereby it is possible to see which nodes have the greatest impact on any selected target node. To gain more insights into the operation and disruption states of the OEM, we perform a sensitivity analysis on the state of the OEM with respect to each supplier. From a purely visual perspective, the length of the bars corresponding to each supplier can be thought of as a measure of the impact the supplier has on the target (OEM). Figure 12a depicts the impact of each supplier on the disruption of the OEM. The vertical line on the horizontal axis depicts the crossover point when a supplier goes from operational state to a disrupted one. For example, the probability of the OEM being disrupted given the result of supplier 2 goes from 7.4% (when supplier 2 is operable) to 21.5% (when supplier 2 is disrupted). Suppliers

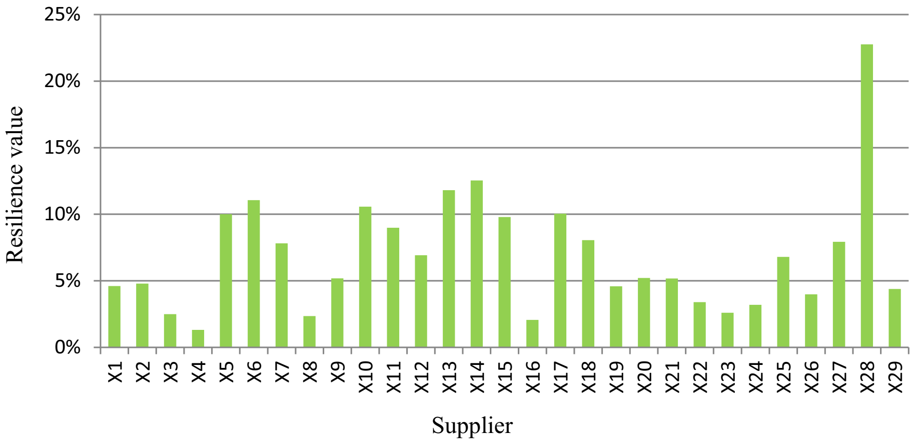

Fig. 10 The resilience value of OEM with respect to each supplier *i*

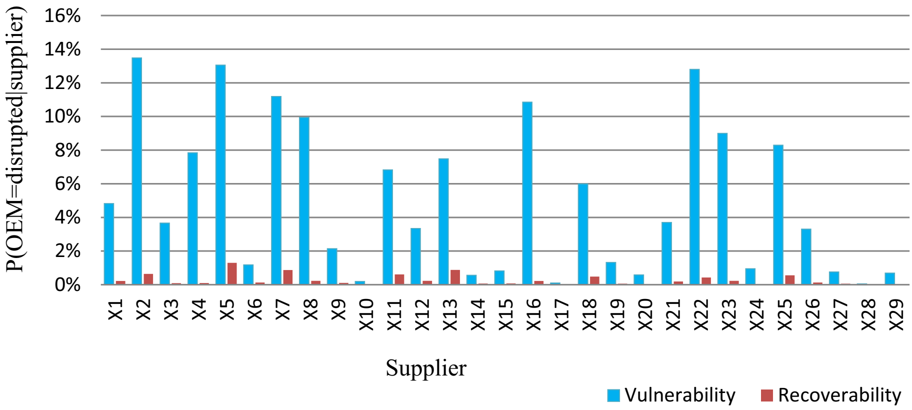

Fig. 11 Vulnerability and recoverability of supplier *i* on OEM

2 and 5 have by far the most impact on the OEM. Figure 12b on the right depicts the impact of each supplier on the operability of the OEM and represents the complement of Fig. 12a.

5.2 Node force visualization of supply network

Here we perform node force analysis to explore the strength of suppliers and the OEM. Node force is used to examine the overall influence of each node, which roughly represents the strength of correlation of a variable with the rest of the nodes in the BN.

The node force of the suppliers is graphically depicted in Fig. 13, where the size of each node is proportional to its node force: the higher node force per node is, the more strength the node has in the BN. Further, the thickness of the arc between nodes in Fig. 13 represents the strength of the conditional dependency between those nodes.

The node force visualization in Fig. 13 shows that the OEM has the greatest strength because of its 14 incoming arcs. Supplier 25 has the second highest strength, with one incoming and four outgoing arcs. With regard to arc thickness, suppliers 25 and 21 are strongly

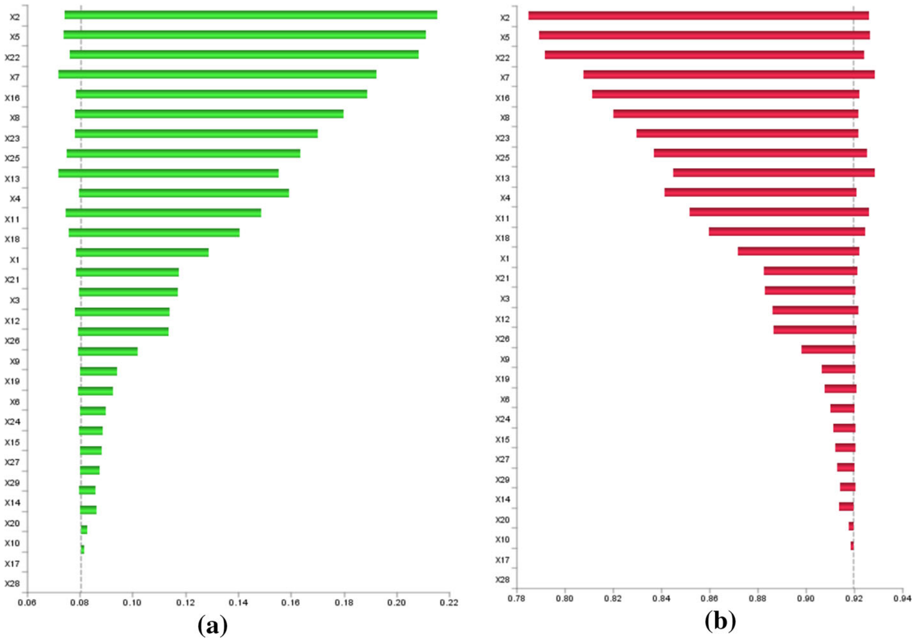

Fig. 12 **a**, **b** Sensitivity analysis graph showing which suppliers have the most impact on whether the OEM is True/False

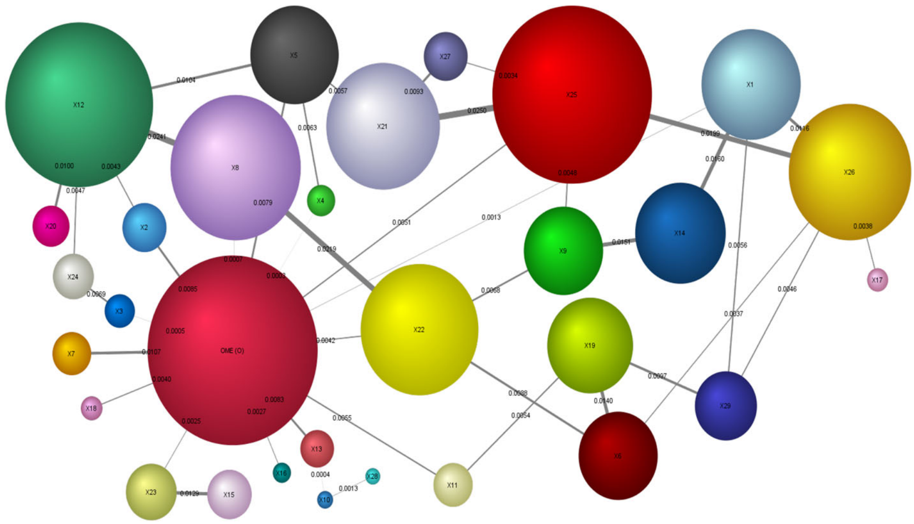

Fig. 13 Node force mapping of supply network

interdependent, with the highest joint probability. There also exists a strong interdependency between suppliers 8 and 22. Note that among first tier suppliers, supplier 7 has the highest interdependency with the OEM.

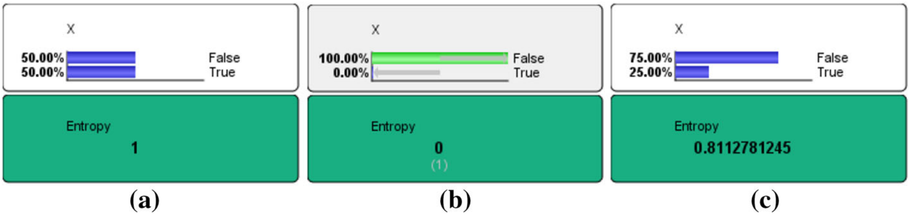

Fig. 14 a–c Entropy value of variable X with different probability distribution cases

5.3 Uncertainty analysis of supplier availability

In a traditional statistical analysis, covariance and correlation between variables are examined to establish their relative importance, specifically with regard to the target variable. Here, we take an alternative approach to investigate the importance of each supplier with regard to the operation of the OEM based on information theory. By applying information theory, we consider how the uncertainty of the states of the OEM is affected by the suppliers.

Beyond a common sense of uncertainty, entropy is used as a key measure of uncertainty in information theory (Wang 2008; Pele et al. 2017). More specifically, we utilize entropy as a tool to measure the uncertainty manifested in the probability distribution of variables (suppliers and OEM) in line with Ivanov and Arkhipov (2011) and Levner and Ptuskin (2017). The entropy for a discrete distribution is defined as a measure of expected log-losses (14):

$$H(X) = -\sum_{x \in X} P(x) log_2 P(x) \tag{14}$$

where $H(X)$ is the entropy of variable X, x is the state of variable X, and $P(x)$ is the probability distribution of variable X on state x. Suppose X is a binary variable with two states of *True* and *False*, $X = \{\text{Yes, False}\}$. The uncertainty of variable X reaches its maximum (1) when the probability distribution of X is uniformly distributed (True $=$ 50%, False $=$ 50%), as illustrated in Fig. 14a. The uncertainty of variable X is at its minimum value of 0 when the probability of either a True or False state is 100%, suggesting that there is no uncertainty involved with variable X, as illustrated in Fig. 14b. Finally, the uncertainty of X with the probability distribution of False $=$ 75% and True $=$ 25% is illustrated in Fig. 14c and the elements of the calculation are shown in Eq. (15).

$$H(X) = -[0.75 \times log_2(0.75) + 0.25 \times log_2(0.25)] = 0.811 \tag{15}$$

Although Eq. (14) is an entropy measure that quantifies the uncertainty involving a single variable X, we are interested in measuring the entropy of X in the context of other variables. As such, mutual information is used to depict how the knowledge of other variables reduces the uncertainty of the variable of interest. In this study, we would like to see how knowledge of supplier i can reduce uncertainty at the OEM. The mutual information between two variables X (predictive variable) and Y (target variable), denoted by $I(Y, X)$ is defined by the difference between the marginal probability of the target variable, $H(Y)$, and the conditional entropy of target variable Y given predictive variable X, $H(Y|X)$ (16),

$$I(Y, X) = H(Y) - H(Y|X) \tag{16}$$

To demonstrate the calculation of mutual information, consider a supplier as the predictive variable and the OEM as the target variable. The prior probabilities of the supplier being disrupted and operational are 0.12 and 0.88, respectively, as illustrated in Fig. 15. Assume

Fig. 15 Prior and marginal probability distributions of the supplier and OEM

Table 4 Conditional probability table (CPT) of OEM disruption

Supplier	False	True
False	0.98	0.02
True	0.11	0.89

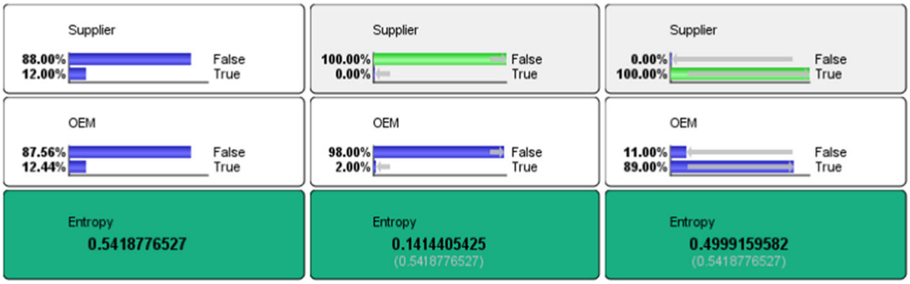

Fig. 16 Entropy of OEM, H(OEM) and marginal entropy of OEM given the supplier, H(OEM|Supplier)

Table 4 represents the CPT of the OEM given the supplier. The marginal probability distribution of the OEM illustrated in Fig. 15 is calculated with Eq. (17) (Fig. 16).

$$H(\text{OEM}) = -[0.8756 \times log_2(0.8756) + 0.1244 \times log_2(0.1244)] = 0.5419 \tag{17}$$

$$\begin{aligned} H\left(\text{OEM|Supplier}\right) &= P\left(\text{Supplier} = \text{False}\right) \times H\left(\text{OEM|Supplier} = \text{False}\right) \\ &\quad + P\left(\text{Supplier} = \text{True}\right) \times H\left(\text{OEM|Supplier} = \text{True}\right) \\ &= (0.88 \times 0.141) + (0.12 \times 0.499) = 0.184 \end{aligned} \tag{18}$$

$$I(\text{OEM, Supplier}) = H(\text{OEM}) - H(\text{OEM|Supplier}) = 0.5419 - 0.184 = 0.3579 \tag{19}$$

The mutual information of OEM and supplier is 0.357 as calculated in Eq. (19), suggesting that knowledge about the supplier can reduce uncertainty at the OEM by 35.7%. Mutual information can effectively measure the uncertainty associated with the variable of interest regardless of what type of relationship (linear or nonlinear) exists between those two variables.

The intuitive interpretation of mutual information in this study is that a supplier that reduces more uncertainty with regard to the OEM is more important. The mutual information measure can provide a complementary perspective to the resilience metric. We plot importance versus resilience in the multi-quadrant chart in Fig. 17.

The multi-quadrant chart offers us a convenient way to identify which suppliers are important, but less resilient. This plot is divided into four quadrants. One could surmise that the most critical suppliers are the ones located in the upper left quadrant (suppliers 2, 9, 19, 21, 22, 26), since they are highly important with regards to the OEM, but not sufficiently resilient. As such, the OEM can look to other suppliers to take their place or request that they improve their pre-disaster and post-disaster resilience strategies to reduce the risk of

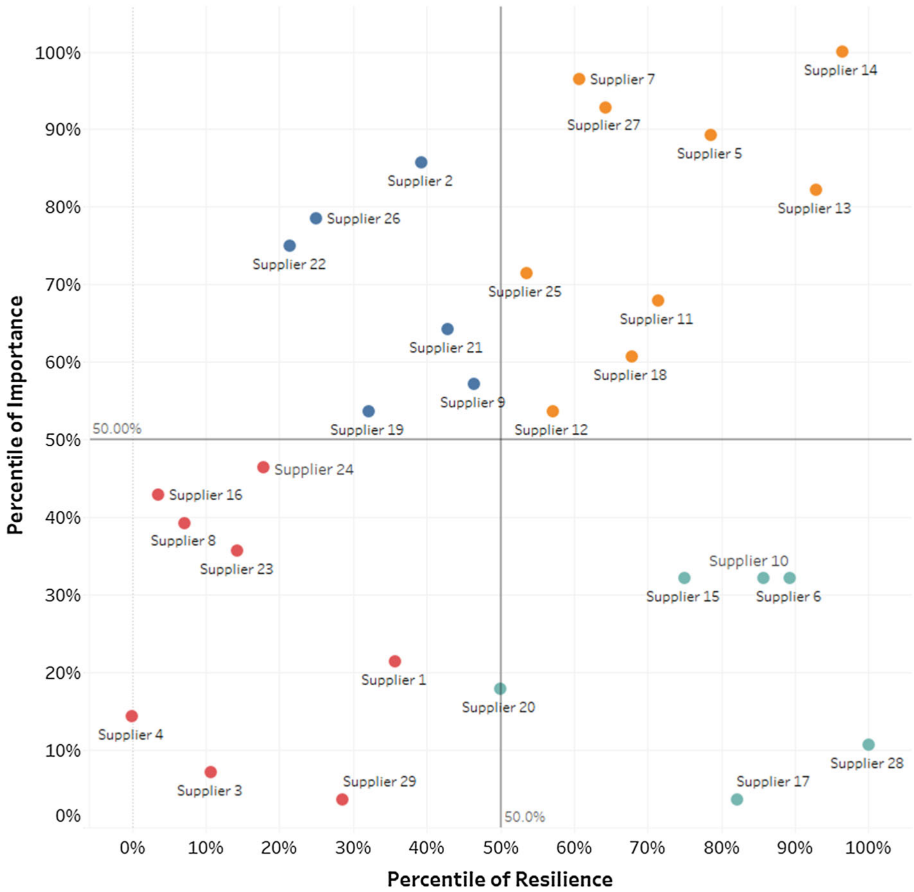

Fig. 17 Quadrant plot analysis of resilience and supplier importance

disruption propagation throughout the supply network. Suppliers located in the upper right quadrant are also considered important but probably do not need major revisions in their resilience strategies. Finally, suppliers located in the lower left quadrant lack resilience, but are not as important as other less resilient suppliers.

6 Managerial insights

The approach developed in this paper allows the resilience of OEMs to be measured by analyzing the resilience of suppliers in multi-tier supply networks, rather than by measuring disruption-resistance at the OEM itself. As such, the proposed approach can be explicitly used to analyse the proneness of the SC to the ripple effect and to control this effect by re-designing the supply base. Our approach and the new resilience metric can guide the firms in the ripple effect control by uncovering the most critical suppliers the disruptions at which greatly contribute to the ripple effect. In complex SCs with large number of suppliers, it is critical for OEMs to identify the resilience levels of their most important suppliers.

Increasing the resilience of the most important suppliers can have a significant impact on OEM disruption risk reduction.

Our model allows for a number of substantive managerial insights. First, it constructs an explicit measure of the OEM resilience using the analysis of suppliers' risk resistance in multi-tier supply networks rather than the resistance to disruption of the OEM itself. Second, we introduce metrics that quantify the resilience of suppliers as a compounded function of their vulnerability and recoverability using a BN and considering disruption propagation. Such a combination is unique in literature. It mimics the complexity of business reality affording more realistic applications to making strategic sourcing decisions. In this paper, we proposed vulnerability and recoverability metrics to assess SC exposure to disruptions. The vulnerability metric quantifies how much the level of disruption risk at the OEM increases when a given supplier is disrupted. The recoverability metric quantifies how much the level of disruption risk decreases at the OEM when a given supplier is fully operational. The resilience of the OEM with respect to the supplier is then defined as a ratio of recoverability to vulnerability. Such a resilience metric can capture the ripple effect of supplier disruption propagation throughout the supply network via the causal inference property of BN.

The findings suggest that our model can be of value for OEMs to identify the resilience level of their most important suppliers based on forming a quadrant plot in terms of supplier importance and resilience. Mutual information theory is used to determine and rank the relative importance of each supplier. We used quadrant plot analysis to compare suppliers with respect to the OEM in terms of their importance and resilience. The plot is divided into four quadrants and suppliers are classified according to their importance and resilience. These classifications can support managers' decision making. Quadrant I includes suppliers that are both important and resilient. As such, those suppliers may not need any major revisions on their resilience strategies. Quadrant II includes suppliers that are important, but not resilient. OEMs should observe the performance of suppliers in Quadrant II more closely and ask them to revise their resilience strategies since they play an important role in the whole supply network. It is notable that increasing the visibility of the OEM to suppliers in Quadrant II can help to improve the vulnerability of supply network. Quadrant III includes suppliers who are less important and have lower levels of resilience. Increasing the resilience level of these suppliers can be considered a second priority as compared to the suppliers located in Quadrant II. Quadrant IV includes suppliers that are less important, but highly resilient, which is a good indication. This indicates that suppliers in Quadrant IV likely do not need major changes to their resilience strategies as compared to the suppliers in Quadrant II and III.

Our method explicitly allows to uncover latent, high-risk suppliers to develop recommendations for sourcing decisions. The resilience assessment developed can be used by managers to mitigate the impact of disruption risks and to make OEMs more resilient to disruptions at suppliers in different tiers. Utilizing the outcomes of this research could support the design of resilient supply networks with a large number of suppliers: critical suppliers with low resilience can be identified and developed. Finally, the identification of the suppliers with a higher contribution to the SC proneness to the ripple effect may be used by decision-makers to analyse so-called "hidden" suppliers to increase the chances to identify the real roots of the ripple effect. The importance of this step was recently highlighted by Shao et al. (2018).

7 Concluding remarks

SCs have become more prone to disruptions due to the globalization of business, complexity and competitiveness of SC structures, and the increasing occurrence of internal and external disruptive events. To ensure continuous operation of SC systems, enterprises and stakeholders must be prepared for disruptive events with the capability to enact a quick response and a high capacity for recovery from disruptive events. Complex supply networks, like those in the automobile and aerospace industries, with a large number of global and local suppliers can be even more vulnerable, because of the ripple effect. Hence, it is important for manufactures to have more visibility in regards to vulnerable second and third tier suppliers, not only first tier suppliers.

This study assesses the OEM exposure to the disruption propagation in its supply network. We contribute to literature by constructing a new measure that quantifies the resilience of the OEM with a multi-stage assessment of suppliers as a function of their vulnerability and recoverability using a BN and considering disruption propagation. Information theory is employed to rank the importance of suppliers. We proposed a methodology that exploits BN to assess SC resilience with disruption propagation while avoiding two major inconveniences, namely the numerous dependencies among the SC tiers and modeling the impact of rare disruptive events.

Our study conceptualizes and models a unique and comprehensive SC resilience measure that in turn, feeds an explicit quantification of SC disruption propagation exposure. The constructed supplier plot is divided into four quadrants so that risk-oriented suppliers can be classified and corresponding recommendations for supplier management developed. For example, suppliers with a low degree of resilience and high importance can be identified. Such a vulnerability analysis of suppliers can help to mitigate the disruption risk of supply networks and make OEMs more resilient to disruptions at suppliers in different tiers. The outcomes of this research can therefore be applied to the design of resilient supply networks which have large numbers of suppliers. We provided theoretical implications and managerial recommendations for identifying and improving SC resilience using forward and backward disruption propagation analysis.

The results of this research can be utilized for decision support models, contributing to major theoretic domains in supplier management such as resilient supplier selection, assessment and development. The vulnerability analysis of suppliers can help firms to mitigate the disruption risk impact by re-designing the supplier base and developing most critical suppliers making OEMs more resilient in the event of disruptions at different tiers. With the results of this study, it becomes possible to measure the resilience of OEMs by analyzing the resilience of suppliers in multi-tier supply networks and to mitigate the ripple effect.

Our study has a few limitations. One issue is that we model the downstream ripple effect propagation and exclude the upstream disruption propagations which might be possible, e.g., in case of an OEM disruption and its just-in-time suppliers. Another limitation is an implicit consideration of disruption probabilities which might be a challenging task in practical decision environments.

Future research can investigate the disruption cost of a disrupted supplier on an OEM using utility cost theory and BN theory. Moreover, the detailed case-study analyses of Quadrants I–IV in different industries and services may help to reveal some specific factors and generalizations of the approach developed. Finally, the increasing use of digital technology in SCs can be considered in the future with regards to the sourcing strategy decisions.

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