UOK-LM-18-226

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Improved Acquisition for System Sustainment: Resilient Supplier Evaluation and Selection with Bayesian Networks

30 August 2018

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Disclaimer: This material is based upon work supported by the Naval Postgraduate School Acquisition Research Program under Grant No. N00244-17-1-0005. The views expressed in written materials or publications, and/or made by speakers, moderators, and presenters, do not necessarily reflect the official policies of the Naval Postgraduate School nor does mention of trade names, commercial practices, or organizations imply endorsement by the U.S. Government.

Prepared for the Naval Postgraduate School, Monterey, CA 93943.

The research presented in this report was supported by the Acquisition Research Program of the Graduate School of Business & Public Policy at the Naval Postgraduate School.

Abstract

Supply networks have become more susceptible to disruptions due to a number of factors, including their increasing interconnected structure, the continued growth of global supply alternatives, and strategic outsourcing. Multi-tier supply networks in aerospace and automotive industries are particularly more exposed to disruptions, because the continuity of operations of manufacturers is highly vulnerable to disruptions of their suppliers (and of their suppliers' suppliers, and so on). This paper aims to measure the resilience of manufacturers by analyzing the resilience of suppliers in multi-tier supply networks. As a result, suppliers that adversely impact the resilience of a manufacturer are highlighted, and other candidates for suppliers can be examined. We introduce metrics that quantify the resilience of suppliers as a function of their vulnerability and recoverability and quantify these metrics using Bayesian networks. Information theory is discussed as a means to rank the importance of suppliers.

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Table of Contents

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List of Figures

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List of Tables

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Introduction

Due to rapid globalization of supply chain alternatives and evolution of strategic outsourcing, understanding and measuring disruptions to supply networks has become an important area of study. The objective of supply networks has expanded beyond short term cost savings to long term strategic benefits like achieving high level of resilience. Hendricks and Singhal (2005) stated that the announcement of a supply disruption could drop a firm's stock by an average of 20% six months after the announcement. Recent industry examples highlight the need for manufacturing firms to recover quickly after disruptions. For example, the Japanese tsunami and earthquake had profound implications on global supply chains, inventory levels, profit margins, corporate bottom lines, and broad economic output (ZeroHedge 2011). Many of Toyota's part suppliers were unable to deliver parts at their expected volume and suffered from significant delays. Toyota was forced to keep some plants in North America idle due to shortage of parts also halted most operations at 18 factories that assemble Toyota and Lexus vehicles in Japan (Huffington Post 2015, Ferreira 2012). 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 2016). The impact of the Japanese disruption was not limited to the auto industry solely but also expanded to other industries like electronics where, for example, Sony suffered from shortages of electronics parts and raw materials, which forced them to suspend the production at five plants in central and southern Japan producing camera lenses, televisions, and other goods (ZeroHedge 2011). These examples highlight that natural disasters could pose serious risks to automakers like Toyota which implements lean production methods and just-in-time supply chains. Balancing the (i) vulnerability of lean production and just-in-time systems and (ii) the high cost of maintaining large inventories require manufacturers to focus on the ability to respond flexibly to disruptions.

Many of the recent studies of resilient supply chain networks have focused on assessing the vulnerability of manufacturing firms or capabilities necessary to manage disruptions (Ellis et al. 2010; Sheffi 2007). However, in many cases, supply disruptions (i.e., stoppage of raw material supply) are not caused at a manufacturing firm's facilities, but rather from its supply networks (Kim et al. 2015). Analyzing disruptions causing discontinuity of supply network could be challenging for several reasons. First, dependencies among the occurrence of disruptive events must be tracked. For example, earthquakes and tsunami are closely related. Tsunami can be caused by massive deep-level water displacement which is most common during earthquakes under ocean floor. The Japanese tsunami in 2011 indicates that the dependency among tsunami and earthquake and its impact on manufacturing industries was not explored very well. Second, researchers and industry practitioners largely focus to measure the vulnerability of manufacturing firms and first tier of their suppliers due to the complexity and large number of suppliers, while a true vulnerability analysis of supply networks can be accomplished when the impacts of disruption caused by supplier's supplier (tier 2 and tier 3 suppliers) are quantified throughout the supply networks. Third, suppliers can be disrupted due to operational, financial or environmental disruptive events. Snyder et al. (2010) discuss common modeling approaches of supply chain disruptions, but most of these models account for specific decision making situations such as how much to keep as surplus inventory.

In this paper, we propose a methodology that integrates Bayesian networks (BNs) and optimization to quantify the resilience of supply networks. BNs are capable of describing the causes and effects of system output using 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; Li et al. 2016; Hosseini and Barker 2016a,b; Qazi et al. 2017; Liu et al. 2018). The proposed metric measures the resilience of manufacturing firms as a function of the vulnerability and recoverability of their direct and indirect suppliers. We provide theoretical and managerial implications to identifying and improving the resilience of supply chain networks using forward and backward propagation analysis.

The rest of this paper is organized as follows: Section 2 reveals the literature review of supply chain resilience and disruptions. Section 3 discusses the theory of BN. New metrics to quantify resilience of supply networks is presented in Section 4. The analysis of simulation results are discussed in Section 5, finally the conclusion is given in Section 6.

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BACKGROUND AND LITERATURE REVIEW

A supply chain disruption is defined as an unanticipated and unforeseen disruption that disrupts the normal flow of goods and materials in a supply network (Svensson 2000, Hendrick and Singhal 2003, Craighead et al. 2007). Longo and Oren (2008) defined supply chain resilience as the probability that a supply chain reacts to internal and external disturbances and returns to an equilibrium state in an efficient manner. A great deal of attention has been devoted to modeling disruptions to and resilience of supply chains from 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., Juttner et al. 2003, Sheffi and Rice 2005, Craighead et al. 2007, Torabi et al. 2015, Hosseini and Barker 2016a), and simulation modeling (Zhao et al. 2011, Nair and Vidal 2011, Carvalho et al. 2012). Carvalho et al. (2012) used discrete event simulation to model automotive supply chain disruptions, evaluating the impact of different mitigation scenarios on the lead time and total cost of supply chains. Wu et al. (2007) modeled the extent of propagation impact of disruptions throughout supply chains. Brusset and Teller (2017) studied supply chain risks and resilience using structural equations modeling (SEM). Their work reveals that (i) tighter integration between echelons and increasing supplier and manufacturing flexibility can significantly enhance the resilience, and (ii) the perception of external disruption risks to supply chains can actually decrease the effort of deploying external capabilities to achieve resilience. Park et al. (2016) also utilized SEM to examine the causal relationship between risk taking propensity and supply chain disruption occurrences. Mancheri et al. (2018) developed a system dynamic simulation model to measure the resilience and vulnerability of a supply chain and found several resilience-enhancing mechanisms, including diversity of supply, material substitution, recycling, and stockpiling. Garvey et al. (2015) proposed an analytical framework to investigate the interdependencies of various risks in supply chains. Shin et al. (2011) examined the impact of alternative backorder replenishment plans on expected risk. Bode and Wagner (2015) studied the effect of complexity and structure of upstream supply chain (supply-side) on the occurrence of disruptions, showing that the several drivers of complexity (i.e., horizontal, vertical, and spatial complexity) increase the frequency of disruptions. Blackhurst et al. (2018) used Petri nets and clustering algorithms to analyze a supply chain network's vulnerability and evaluate different mitigation strategies in the case of supply chain disruptions. Snyder et al. (2010) and Sodhi et al. (2012) investigated the effects of different mitigation strategies such as buffer inventory, order reallocation on supply chain disruptions. Schemitt and Singh (2011) utilized simulation modeling approach to evaluate the impact of disruptions on dynamic supply networks. Schemitt et al. (2017) studied how adjustments in order activities could help to a quicker recovery from disruption, showing that adaptive ordering as a mitigation tool can trigger an unintended bullwhip effect. Carbonara and Pellegrino (2017) developed a computational model to measure the value of a postponement strategy in mitigating both demand and supply disruptions.

Hosseini and Barker (2016a) developed a BN to evaluate suppliers based on primary, green, and resilience criteria, identifying factors that contribute to the resilience capacity of and probability of disruption of suppliers. Hosseini et al. (2016d) proposed a generic framework that consists of five phases: (i) threat analysis, (ii) resilience capacity design, (iii) resilience cost evaluation, (iv) resilience quantification, and (v) resilience improvement to design resilient supply chain systems. The authors simulated the impact of several environmental disruptions on the performance of manufacturing site using BN method. In this work, we utilize BN to model the dependencies among suppliers and manufacturers, and we propose metrics to quantify the vulnerability, recoverability, and resilience of a manufacturer in large scale supply networks. The vulnerability metric propagates the impact of a supplier disruption to the manufacturer, 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 its recoverability to vulnerability.

Bayesian Networks

BNs have been recognized as a powerful technology for dealing with uncertainty, handling risk assessment, and aiding the decision making process. BNs have been extensively utilized as a decision support tool in a diverse set of application domains such as risk analysis (Song et al. 201, Smith et al. 2017, Kabir et al. 2018), reliability engineering (Langseth and Portinable 2207, Marquez et al. 2010), medical diagnosis support (Petousis et al. 2016, Constantinou, et al. 2016), infrastructure resilience (Hosseini and Barker 2016a,b, Hosseini et al. 2016d), and decision making (Sierra, et al. 2018, Sturlaugson et al. 2017), among others. BNs are particularly useful for risk analysis of complex systems for two main reasons: (i) there are numerous dependencies among the components of complex system which can be easily modeled using BNs, and (ii) BNs are capable of combining historical data and expert knowledge when there are a little 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 advantages of BNs can be found in Uusitalo (2007), Boutselis and McNaught (2018), 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 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 directed acyclic graph represented by *G,* where $G = (V, E)$ and $V = \{X_1, X_2, \dots, X_n\}$ represents a set of random variables and *E* is 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: (i) nodes without any child that are called *leaf nodes*, (ii) nodes without any parent node are called *root nodes*, and finally (iii) those nodes with parent and child nodes are called *intermediate nodes*. For example, in Figure 1, X_2 and X_3 are root nodes, X_4 is the leaf node and X_1 is intermediate node.

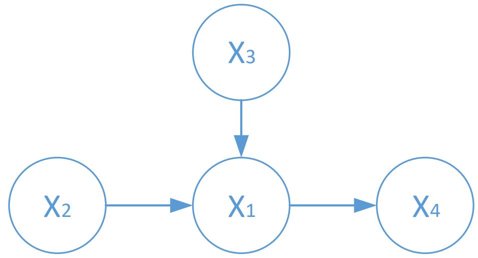

Figure 1. An illustrative example of BN with four variables

The dependency between a child node with their parent nodes can be quantified by a conditional probability table (CPT). For the nodes without any parent, unconditional probabilities (UPs) 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 $X_1, X_2, \dots, X_n$. The general expression for joint probability distribution can be represented as follows:

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

Eq. (1) can be rewritten with Eq. (2).

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

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

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

The full joint probability distribution for the illustrative example depicted in Figure 1 can be written with Eq. (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 node (variable) can be computed by the marginalization of the joint probability distribution. For example, the formula for marginalization of variable X_2 is found in Eq. (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 the global joint probability can be performed by marginalizing the local node probability. For example, $P(X_2)$ from Figure 1 can be calculated with Eq. (6).

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

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PROPOSED RESILIENCE METRIC

This section describes the resilience metric calculated for manufacturers as a function of supplier vulnerability and recoverability.

Modeling a Supply Network Disruption

As discussed earlier, BNs are acyclic directed networks with a set of nodes (variables) and arcs. A raw material flow supply can be modeled using BN, where each node or variable represents a supplier and direction of material flow captured by an arc direction. We assume that the rate of return flow is negligible, so there are no cycles in the network. The relationship $X \rightarrow Y$ represents that material flow supplied from supplier X_1 to X_2 supplier *Y*. This also means that a disruption of supplier X_1 can cause a disruption of supplier X_2, as materials flow from supplier X_1 to X_2. While an upstream supplier can disrupt a downstream supplier (e.g., X_1 disrupting X_2), it is assumed that a disrupted downstream supplier will not disrupt an upstream supplier.

Represent supplier node *i* with X_i in a supply network with suppliers, $i = 1, \ldots, n$, and the manufacturer is denoted by *O* (this is also the target or sink 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.

Consider a simple BN model consisting of one manufacturer (node *O*) and two supplier nodes (X_1, X_2) as represented in Figure 2. Node *O* is conditioned on supplier nodes X_1 and X_2, which means that the disruption of either supplier can cause the disruption of the manufacturer. The prior probability of each supplier is assumed to be 3%, suggesting each supplier can fail to supply to the manufacturer with the likelihood of 3%. Disruption of a supplier induces disruption at *O* with a specific probability. Table 1 lists the conditional probabilities of disruption at the manufacturer due to the disruption of supplier *i*.

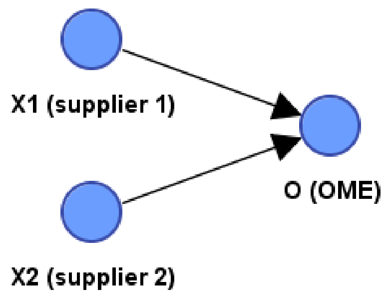

Figure 2. A simple BN with two suppliers and one manufacture

Table 1. Conditional probability table (CPT) of a manufacturer disruption

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

According to Table 1, for example, the probability that the manufacturer is disrupted if supplier 1 is disrupted and supplier 2 is operational is 0.12, while this probability changes to 0.21 when both suppliers are disrupted.

The prior and joint distribution probabilities of suppliers and the manufacturer are represented in Figure 3. The marginal probability of a manufacturer disruption, calculated from the conditional probabilities illustrated in Table 1, is 1.54%, which is calculated based on Bayes' theorem from Eq. (6).

$$\begin{aligned}
&P(O\,\text{disrupted}) = \sum_{X_1,X_2} P(\text{Supplier disrupted } | X_1, X_2) \times P(X_1) \times P(X_2) = \\
&P(O\,\text{disrupted}|\ X_1 = \text{disrupted}, X_2 = \text{disrupted}) \times P(X_1 = \text{disrupted}) \times P(X_2 = \text{disrupted}) + \\
&P(O\,\text{disrupted}|\ X_1 = \text{disrupted}, X_2 = \text{operational}) \times P(X_1 = \text{disrupted}) \times P(X_2 = \text{operational}) + \\
&P(O\,\text{disrupted}|\ X_1 = \text{operational}, X_2 = \text{disrupted}) \times P(X_1 = \text{operational}) \times P(X_2 = \text{disrupted}) + \\
&P(O\,\text{disrupted}|\ X_1 = \text{operational}, X_2 = \text{operational}) \times P(X_1 = \text{operational}) \times P(X_2 = \text{operational}) \\
&= (0.21\times0.03\times0.03)+(0.12\times0.03\times0.97)+(0.08\times0.97\times0.03)+(0.01\times0.97\times0.97)=1.54\%
\end{aligned} \tag{6}$$

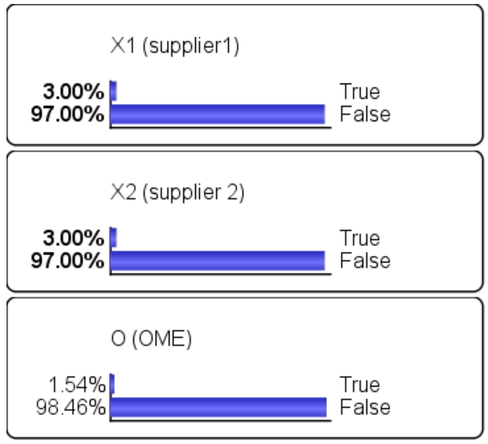

Figure 3. Prior probabilities of two suppliers and marginal distribution probabilities of the manufacturer calculated using CPT

Note that the CPT of a manufacturer disruption represented 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 a manufacturer disruption can be challenging because the manufacturer may receive materials from many suppliers, meaning that the disruption of the manufacturer is conditioned on the disruption of many suppliers. To deal with this issue, we utilize the noisy-OR model (Pearl, 1988) 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: (i) it significantly reduces the computational efforts in large supply networks, particularly when the manufacturer conditions on dozens of suppliers, and (ii) the number of required elicitation probabilities is much less relative to a BN is built using a CPT.

Suppose that there are *n* suppliers, $X_1, X_2, \dots, X_n$, that affect the status of *O*. 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 follows:

$$NoisyOR(X_1, v_{O|X_1}, X_2, v_{O|X_2}, \dots, X_n, v_{O|X_n}, \theta_O) \tag{7}$$

where for 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 manufacturer being disrupted if and only if the *i*th supplier is disrupted solely and other suppliers are operational. There is a leak variable, θ, that represents the probability that the manufacturer is disrupted when all of suppliers are operational. The leak variable is taken into account because the disruption of the manufacturer does not only depend 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 follows:

$$\theta_O = P(O = \text{disrupted} \,|X_1 = \text{operational}, X_2 = \text{operational}, \dots, X_n = \text{operational}) \qquad (8)$$

By applying noisy-OR model, we assume that each supplier operates independently of others in terms of their effects. To see how to utilize noisy-OR model, consider the same example of two suppliers 1 and 2 that feed materials to the manufacturer. The conditional probability of a disruption of the manufacturer due to disruption at supplier *i*, $\forall i = 1{,}2$, is represented by $v_{O|\bar{X}_i}$. The leak probability of node *O* is θ. The prior probability of the disruption of supplier *I* is 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 a manufacturer disruption is calculated in Table 2.

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

States g	$P(O\|g)$	$P(g)$
$g_1 = \{\tilde{X}_1, \tilde{X}_2\}$	$\theta_O = 0.05$	$(1-\eta_1)(1-\eta_2) = 0.93$
$g_2 = \{\tilde{X}_1, \bar{X}_2\}$	$1-(1-\theta_O)(1-v_{O\|\bar{X}_2}) = 0.573$	$(1-\eta_1)\eta_2 = 0.039$
$g_3 = \{\bar{X}_1, \tilde{X}_2\}$	$1-(1-\theta_O)(1-v_{O\|\bar{X}_1}) = 0.43$	$\eta_1(1-\eta_2) = 0.029$
$g_4 = \{\bar{X}_1, \bar{X}_2\}$	$1-(1-\theta_O)(1-v_{O\|\bar{X}_1})(1-v_{O\|\bar{X}_2}) = 0.74$	$\eta_1\eta_2 = 0.001$
	$F_O = \sum_g P(O\|g) \times P(g) = 0.082, F_O = 8.2\%$	

In Table 2, there are four states, $g_1, \dots, g_4$. In state g_1, both suppliers are operational, $(\tilde{X}_1, \tilde{X}_2)$. In the second state, the first supplier is fully operational ($\tilde{X}_1$ 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 ($\tilde{X}_2$).

Finally in the fourth state, both suppliers are disrupted, $(\bar{X}_1, \bar{X}_2)$. The probabilities of two suppliers and the manufacturer modeled using noisy-OR model is illustrated in Figure 4. As shown in Figure 4 and Table 1, the probability F_O of manufacturer disruption is 8.2%.

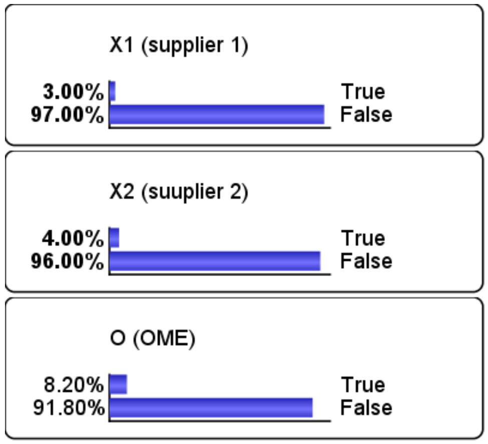

Figure 4. Prior probabilities of two suppliers and marginal distribution probabilities of the manufacturer calculated using noisy-OR model

Proposed Metric for Quantifying the 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*. The performance of system at time *t* is denoted by $\varphi(t)$ in Figure 5. Three transitions states have been used in this model: (i) steady state, where system performs normally at time t_0 prior disruption occurs, (ii), 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 (iii), the recoverability state, where the recovery activity initiates at time t_s and service function of system increases from $\varphi(t_d)$ to $\varphi(t_f)$ at time t_f. Resilience is measured as the ratio of recovery to loss in terms of service function as represented in Eq. (9).

$$Я(t|e^j) = \frac{\varphi(t|e^j) - \varphi(t_\mathrm{d}|e^j)}{\varphi(t_0) - \varphi(t_\mathrm{d}|e^j)} \tag{9}$$

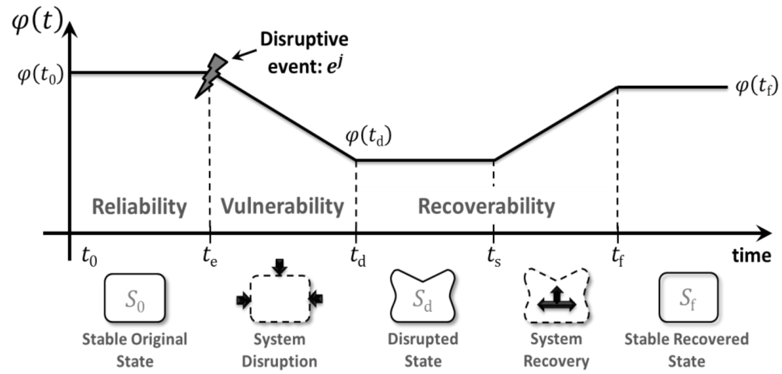

Figure 5. System performance and state transition to describe system resilience (adapted from Henry and Ramirez-Marquez 2012).

The resilience measure can be less than 100% if the recovered level is less than the loss level, equal to 100% if the recovered level is exactly equal to the loss level, and can be greater than 100% if the recovered level is greater than the loss level (e.g., where the performance of the system is somehow improved as a result of recovery).

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

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

$$V_{O|\bar{X}_i} = (F_O(\bar{X}_i) - F_O) \tag{10}$$

The recoverability index $\mathcal{R}_{O|\tilde{X}_i}$ measures the decrease in disruption risk (marginal disruption probability) when supplier *i* is fully operational. To calculate $\mathcal{R}_{O|\tilde{X}_i}$, the state of supplier *i* is changed to 100% False, and the impact is propagated BN to determine the disruption risk of the manufacturer. In essence, the recoverability index quantifies the improvement of disruption risk of the manufacturer corresponding with supplier *i* being fully operational. The recoverability index is calculated with Eq. (11).

$$\mathcal{R}_{O|\tilde{X}_i} = \left(F_O - F_O(\tilde{X}_i)\right) \tag{11}$$

The resilience value of the manufacturer corresponding with supplier *i* is calculated as the ratio of the recoverability and vulnerability indices shown below:

$$Я_{O|X_i} = \frac{\mathcal{R}_{O|\tilde{X}_i}}{V_{O|\bar{X}_i}} = \frac{\left(F_O - F_O(\tilde{X}_i)\right)}{(F_O(\bar{X}_i) - F_O)} \tag{12}$$

To show how to calculate the resilience index, consider a manufacturer 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, and the disruption probabilities of the manufacturer given disrupted suppliers are $v_{O|\bar{X}_1} = 35\%, v_{O|\bar{X}_2} = 40\%, v_{O|\bar{X}_3} = 45\%,$ and $v_{O|\bar{X}_4} = 50\%$, respectively. The probability of the leak variable associated with the manufacturer is $P(\theta_O) = 2\%$. The disruption risk or marginal disruption probability of the manufacturer is then F_O = 9.53%, as illustrated in the baseline BN model in Figure 6. To calculate how much the disruption risk probability of the manufacturer can increase 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 risk disruption of the manufacturer. For example, Figure 7a show that the disruption risk of the manufacturer 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 shown in Table 3. The vulnerability index for supplier 1 is 31.04%, which means that the disruption risk of manufacturer increases by 31.04% when supplier 1 is disrupted or that the vulnerability of the manufacturer 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 of supplier 4 induces more disruption risk to the manufacturer. As such, supplier 4 plays a key role on the disruption risk of the manufacturer. The vulnerability index value can be obtained by performing inference from cause (supplier *i*) to effect (manufacturer) by setting such evidence that supplier *i* is 100% disrupted (True state) and measuring the resulting impact of this observation on the posterior distribution probability of the manufacturer. Considering the illustrative example of the BN model in Figure 6, the probability of the manufacturer being disrupted under normal conditions is F_O = 9.53%, while this probability can increase to $F_O(\bar{X}_1)$ = 40.57% as shown in Figure 8a when supplier 1 is fully disrupted. Figures 8a-d represent the impact of observational inference of the four suppliers on the manufacturer for the BN model given in Figure 6.

A managerial insight of the vulnerability index comparison across four suppliers suggest the importance of reducing the disruption probability of supplier 4 by analyzing the threats that can lead to its disruption and developing a pre-disaster strategy (e.g., extra inventory pre-positioning, fortifying the physical location of supplier) and post-disaster resilience strategies (e.g., contracting with backup suppliers).

The recoverability of the manufacturer with respect to each supplier is calculated using Eq. (11). To calculate $F_O(\tilde{X}_i)$, 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 disruption of the manufacturer. The recoverability index of the manufacturer with respect to each supplier *i* is calculated in Table 3. Finally, the resilience of the manufacturer with respect to each supplier *i* is calculated using Eq. (12).

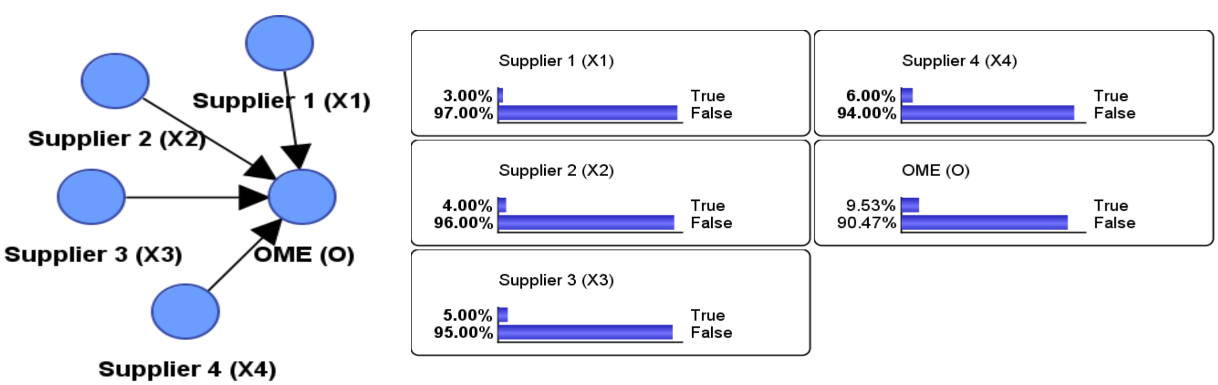

Figure 6. BN model, prior probabilities of four suppliers and marginal disruption probability of the manufacturer.

Table 3. The calculations of the vulnerability, recovery, and resilience indices of the BN model given in Figure 6.

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

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APPLICATION AND EXPERIMENTAL RESULTS

The proposed metrics are illustrated with a 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 manufacturers can have somewhere between 50-1,500 suppliers in the supply base. Hence, analyzing multi-tier supply networks with large number of suppliers and causal relationship among suppliers can be a difficult task. We utilize the noisy-OR formulation to prevent computational burden of analyzing a BN developed for the 29 suppliers of this supply network, as illustrated in Figure 7. The disruption probability of the BN model is extracted from historical data and expert knowledge, as represented in Figure 9. According to Figure 9, the risk of disruption at the manufacturer is $F_O = 8.04\%$.

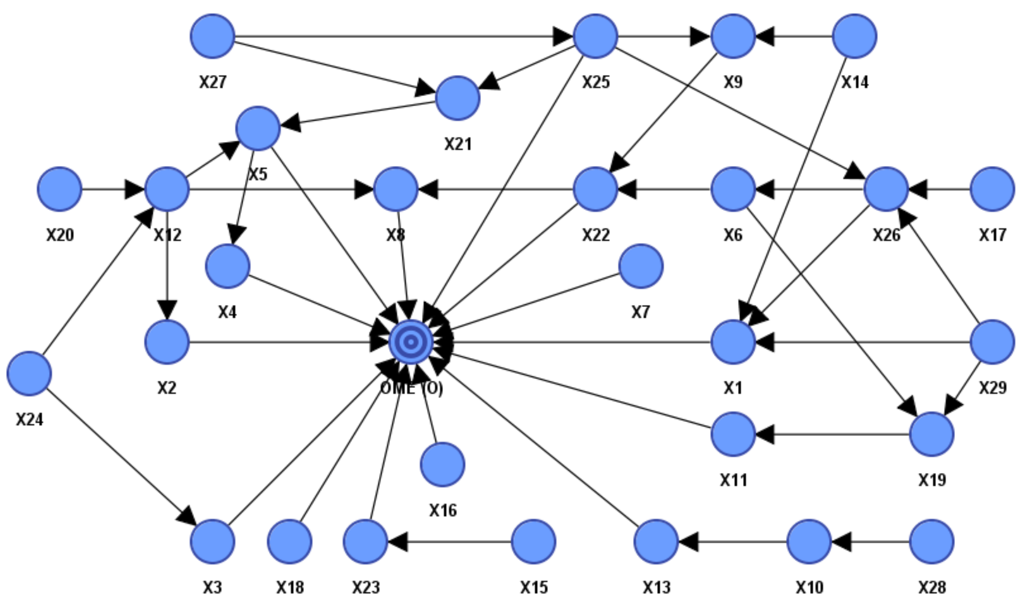


Figure 7. The BN model of center console supply network of Tiba automobile

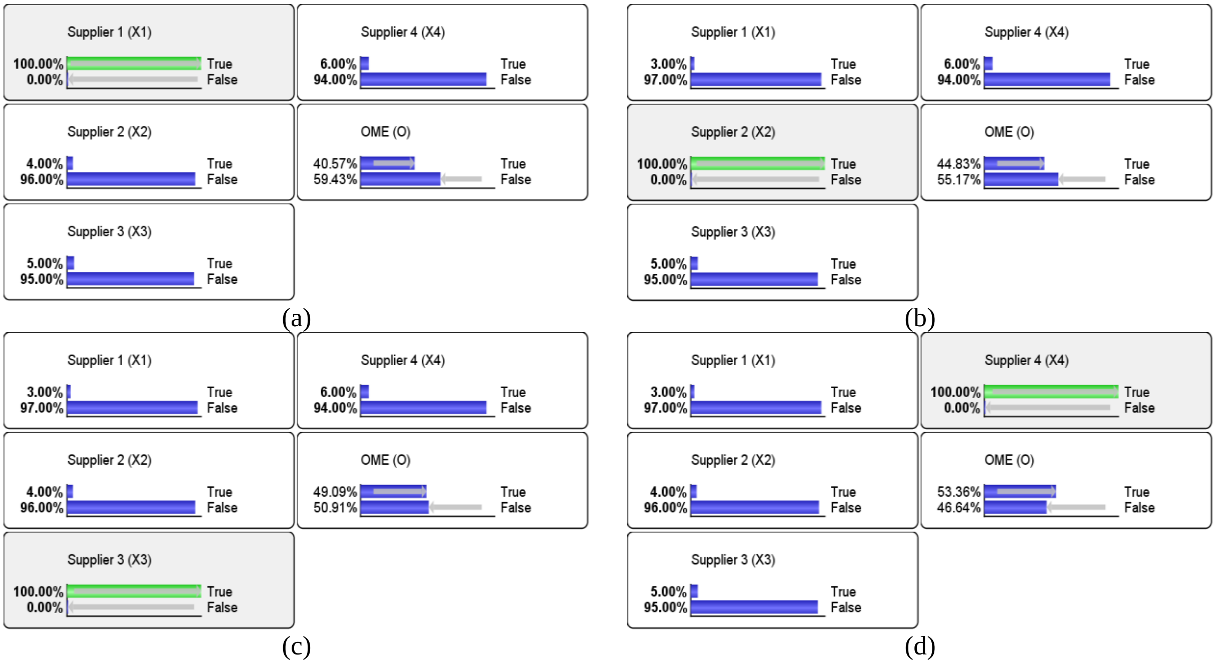


Figure 8. Evidential reasoning of suppliers' disruption for calculating F_O (X¯_i).

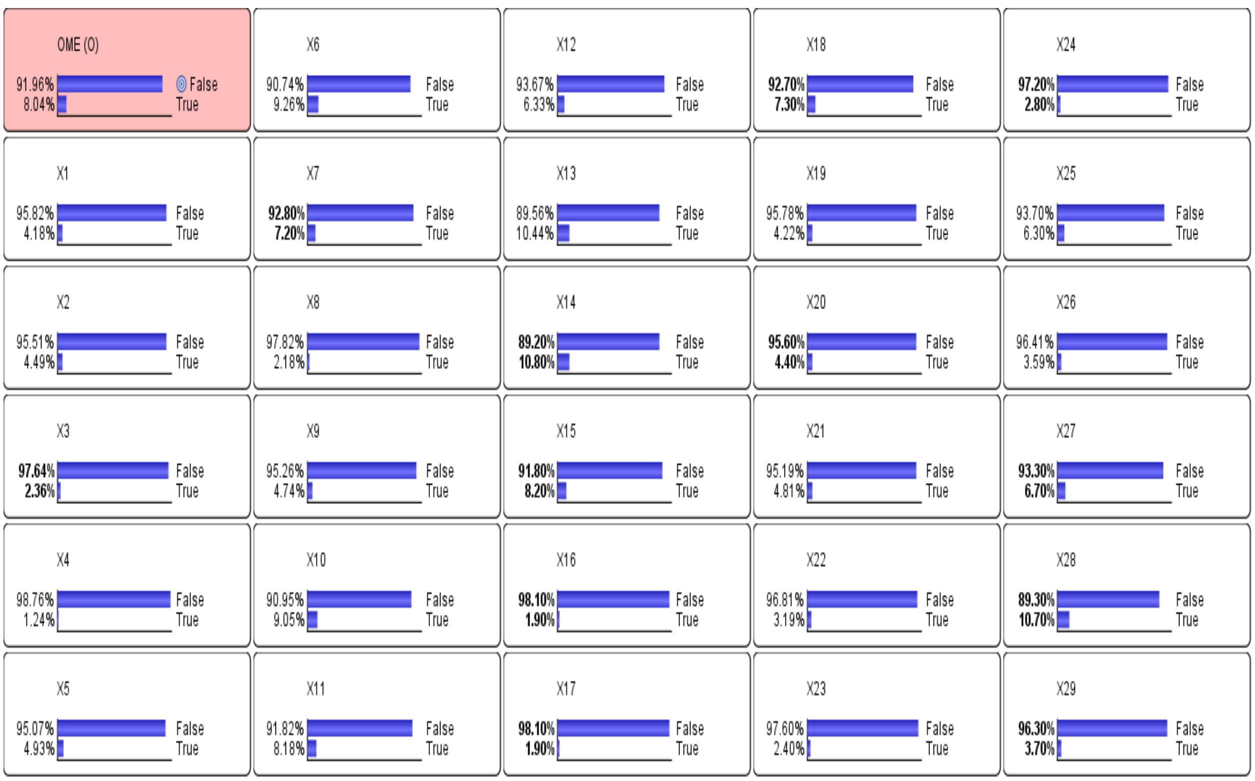


Figure 9. Distribution probability of suppliers and manufacturer for the center console supply network of a Tiba model automobile.

The resilience of the manufacturer with respect to each supplier is illustrated in Figure 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 manufacturer in Figure 7). Figure 11 illustrates the vulnerability and recoverability impact of each supplier on the manufacturer. The result of the vulnerability analysis indicates that a disruption to supplier 2 has the highest impact on disruption of the manufacturer, while the manufacturer is less sensitive to the disruption of suppliers 28, 17, and 10, respectively.

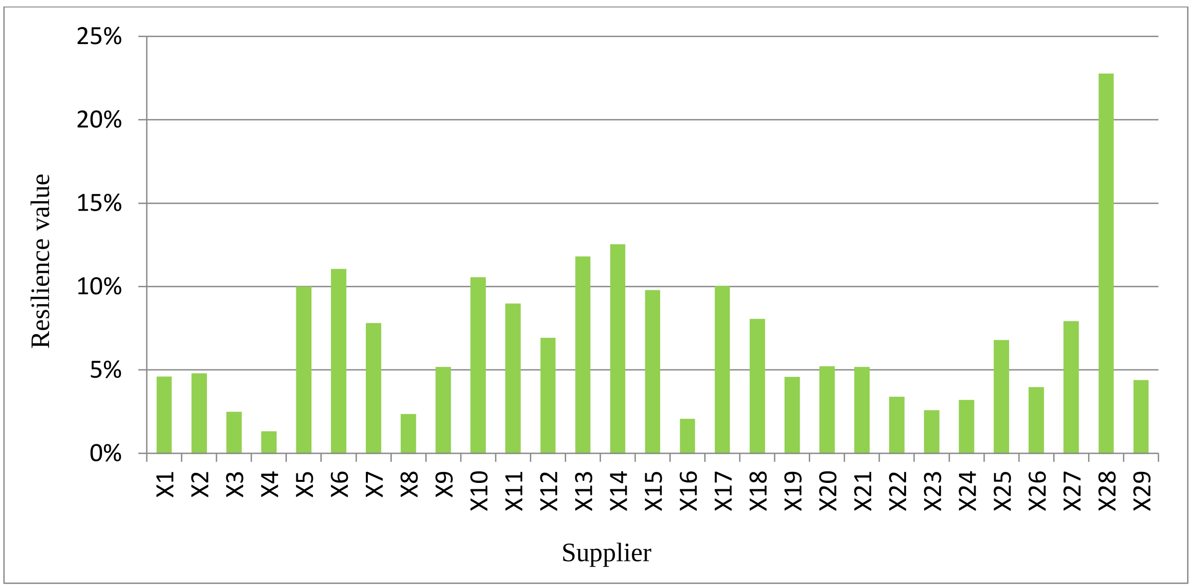


Figure 10. The resilience value of the manufacturer with respect to each supplier.

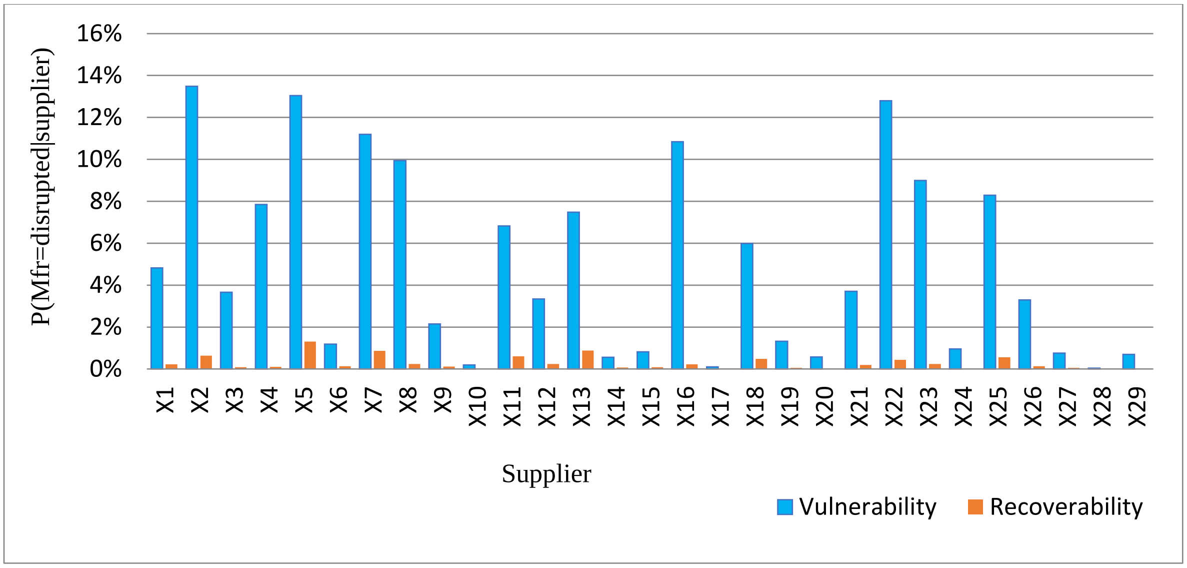
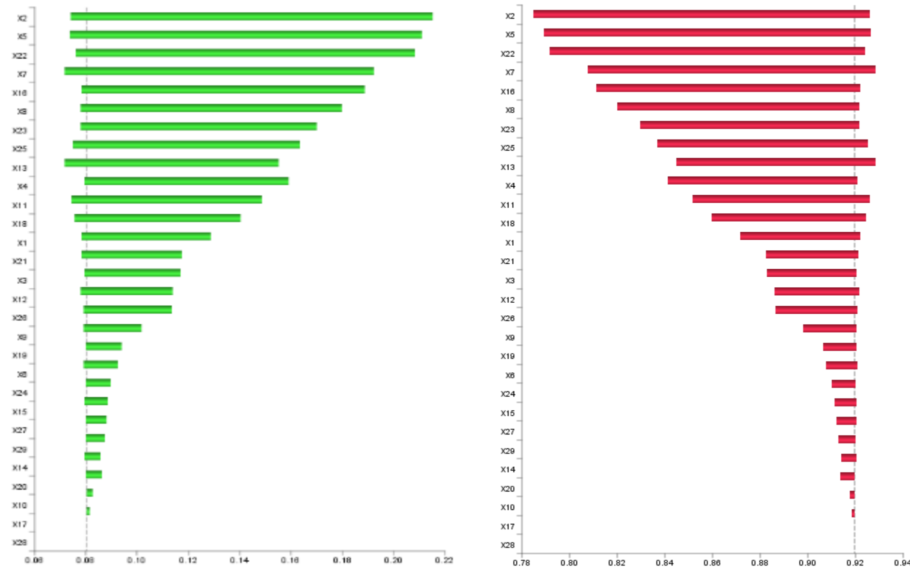


Figure 11. The effect of vulnerability and recoverability of each supplier (individually) on the manufacturer.

Sensitivity Analysis

A useful means to examine the validity of an expert-built model is to perform sensitivity analysis, whereby it is possible to see which nodes have greatest impact on any selected target node. To gain more insights into the operation and disruption states of the manufacturer, we perform sensitivity analysis on the state of the manufacturer 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 of the supplier on the manufacturer. Figure 12a depicts the impact of each supplier on the disruption of the manufacturer. The vertical line at 0.074 on the horizontal axis depicts the crossover of a supplier going from operable to disrupted. For example, the probability of the manufacturer 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 2 and 5 have by far the most impact on the manufacturer. The sensitivity analysis of suppliers on the manufacturer being operable is illustrated in Figure 12b on the right and represents the complement of the Figure 12a.



(a) (b)

Figure 12. Sensitivity analysis graph showing which suppliers most impact on the manufacturer being (a) disrupted and (b) operable.

Node Force Visualization of Supply Network

Here we perform node force analysis to explore the strength of suppliers and the manufacturer. Node force, a heuristic metric that is used to study the importance of suppliers across the entire BN, is defined as the sum of the incoming and outgoing forces. The node force of the suppliers is graphically depicted in Figure 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 is in the BN. Further, the thickness of the arc between nodes in Figure 13 represents the strength of the conditional dependency between nodes.

The node force visualization in Figure 13 shows that the manufacturer has the highest strength due to 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 tightly dependent with the highest joint probability. There also exists a strong dependency between suppliers 8 and 22. Note that among first tier suppliers, supplier 7 has the highest dependency with the manufacturer.

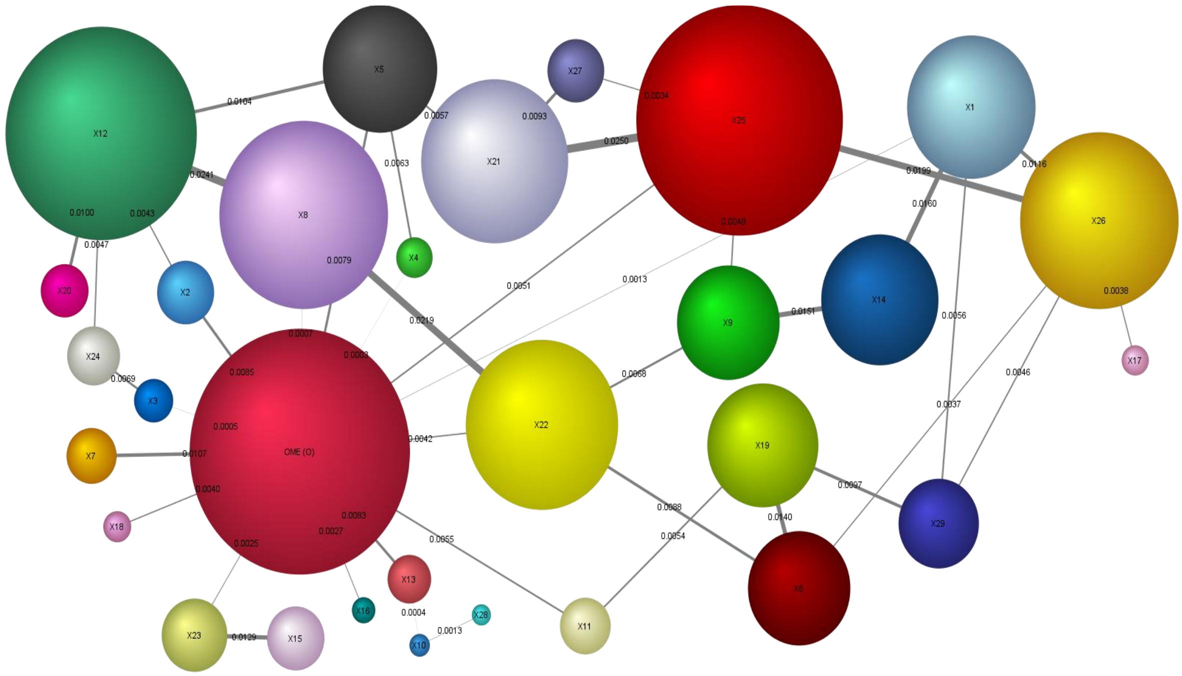


Figure 13. Node force mapping of supply network

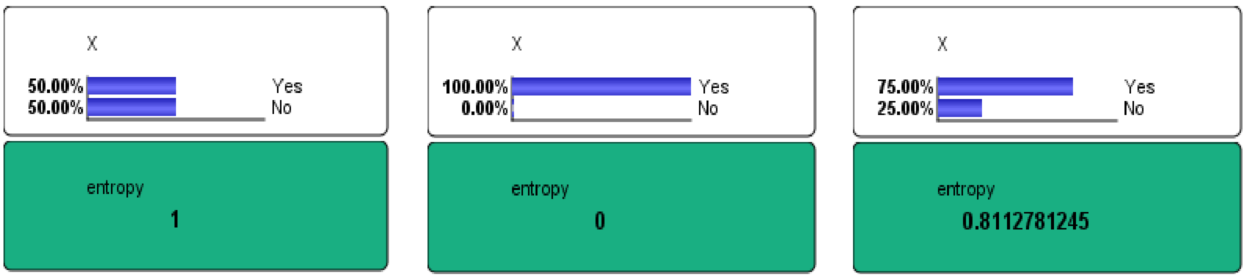
Uncertainty Analysis of Suppliers

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 operability of the manufacturer based on information theory by considering how the uncertainty of the states of the manufacturer is affected by the supplier.

Entropy is 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 the manufacturer. The entropy for a discrete distribution is defined as a measure of expected log-losses, as in Eq. (11), 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*.

$$H(X) = -\sum_{x \in X} P(x) \log_2 P(x) \tag{11}$$

Suppose *X* is a binary variable with two states of True and False, $X = \{\text{True, False}\}$. 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 Figure 14a. The uncertainty of variable *X* is at its minimum value of 0 when the probability of either True or False sate is 100%, suggesting that there is no uncertainty involved with variable *X*, as illustrated in Figure 14b. Finally, the uncertainty of *X* with probability distribution of True=75% and False=25% is illustrated in Figure 14c and the elements of the calculation are shown in Eq. (12).



(a) (b) (c)

Figure 14. Entropy value of variable X with different probability distribution cases

$$H(X) = -[0.75 \times \log_2(0.75) + 0.25 \times \log_2(0.25)] = 0.811 \quad (12)$$

Although Eq. (11) 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 variable reduces the uncertainty of the variable of interest. In this study, we would like to see how the knowledge of supplier *i* can reduce uncertainty on the manufacturer. 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 conditional entropy of target variable *Y* given predictive variable *X*, $H(Y|X)$.

$$I(Y, X) = H(Y) - H(Y|X) \quad (13)$$

To demonstrate the calculation of mutual information, consider a supplier as the predictive variable and the manufacturer as the target variable. The prior probabilities of the supplier being disrupted and operational are 0.12 and 0.88, respectively, as illustrated in Figure 15. Assume Table 4 represents the CPT of the manufacturer given the supplier. The marginal probability distribution of the manufacturer illustrated in Figure 15 is calculated with Eq. (14).

Table 4. Conditional probability table (CPT) of a manufacturer disruption

Supplier	False	True
False	0.98	0.02
True	0.11	0.89

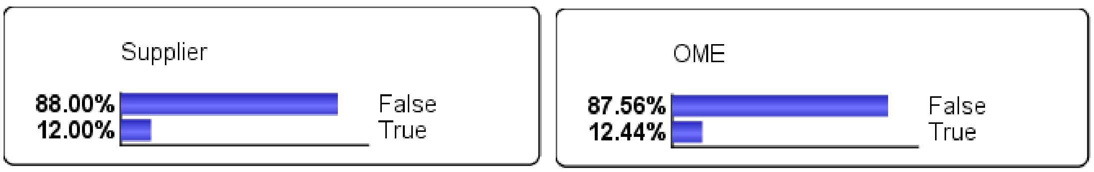


Figure 15. Prior and marginal probability distributions of the supplier and the manufacturer.

$$
\begin{aligned}
H(\mathrm{Mfr}) &= -[0.8756 \times \log_2(0.8756) + 0.1244 \times \log_2(0.1244)] = 0.5419 \\
H(\mathrm{Mfr}|\mathrm{Supplier}) & \\
&= P(\mathrm{Supplier} = \mathrm{False}) \times H(\mathrm{Mfr}|\mathrm{Supplier} = \mathrm{False}) \\
&\quad + P(\mathrm{Supplier} = \mathrm{True}) \times H(\mathrm{Mfr}|\mathrm{Supplier} = \mathrm{True}) \\
&= (0.88 \times 0.141) + (0.12 \times 0.499) = 0.184 \\
I(\mathrm{Mfr}, \mathrm{Supplier}) &= H(\mathrm{Mfr}) - H(\mathrm{Mfr}|\mathrm{Supplier}) = 0.5419 - 0.184 = 0.3579
\end{aligned}
\qquad (14)
$$

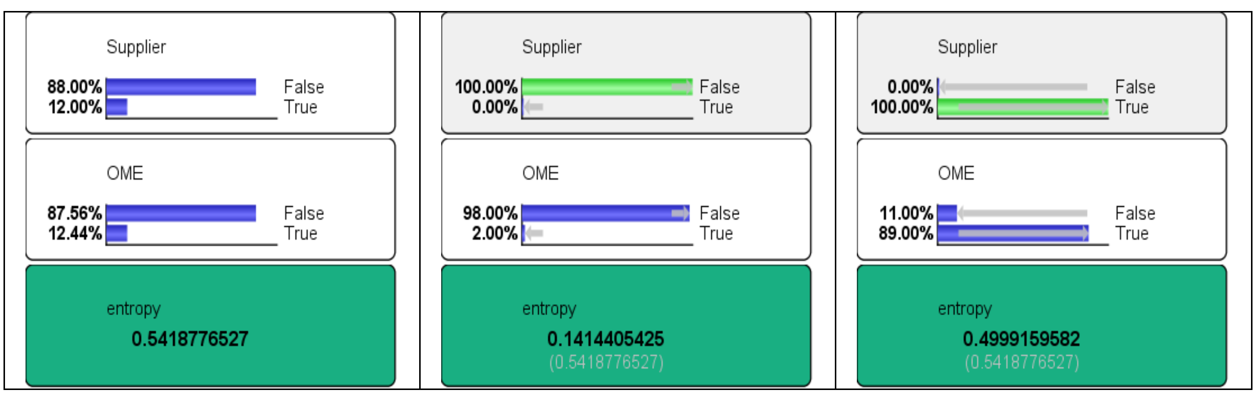


Figure 16. Entropy of the manufacturer and marginal entropy of the manufacturer given the supplier.

The mutual information of the manufacturer and supplier is 0.357 as calculated in Eq. (14), suggesting that the knowledge about the supplier can reduce the uncertainty in characterizing the manufacturer by 35.7%. While the primary focus of this work is to characterize the importance of suppliers on the manufacturer, this approach also enables the evaluation of the importance of lower tier suppliers to top tier suppliers. The mutual information can effectively measure the uncertainty associated with variable of interest regardless of what type of the relationship (linear or nonlinear) existing 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 manufacturer is more important. The mutual information measure can provide a complementary perspective to resilience metric discussed in section 3.2. We plot importance versus resilience in the multi-quadrant chart in Figure 17. This plot divides 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), as they are highly important with regards to the manufacturer but not sufficiently resilient. As such, the manufacturer 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 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 deemed as important as other less resilient suppliers.

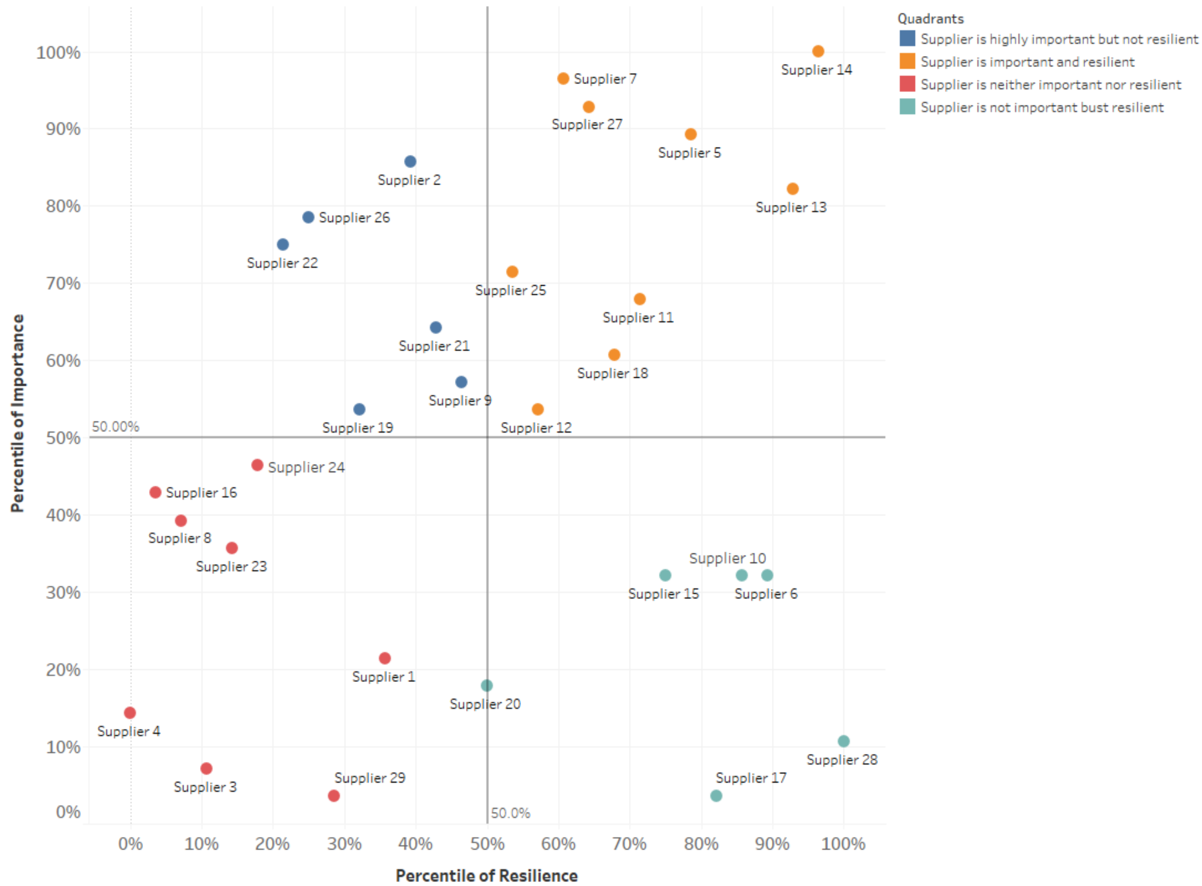


Figure 17. Quadrant plot analysis of percentile resilience versus percentile of importance

Conclusions

Supply chains have become more susceptible to disruptions due to the globalization of business, the complexity and competitiveness of supply chain structures, and the increasing occurrence of major disruptive events. To ensure the continuous operation of supply chain networks, the constituents of the supply chain must be prepared for disruptive events with quick response and high recovery capacity. Complex manufacturing supply networks, like those in the automobile industry that have a large number of local and global suppliers, can be more vulnerable as there exist more opportunities for cascading effects. Hence, it is important for manufactures to have a means to measure the vulnerability and recoverability of not only first tier suppliers, but second and third tier supplier as well.

In this paper, we propose vulnerability and recoverability metrics, the combination of which describe resilience. The vulnerability metric quantifies the change in risk of a disruption of a manufacturer with respect when a particular supplier is disrupted. The recoverability metric quantifies the level of deceases in total risk of disruption of the manufacturer with respect to supplier when supplier is fully operational. The resilience of the manufacturer with respect to supplier is then defined as a ratio of recoverability to vulnerability. The resilience metric can capture the ripple effect of a supplier disruption throughout the supply network by the causal inference property of Bayesian networks. In complex supply chains with large number of suppliers, it is critical for manufacturers to identify the resilience level of their important suppliers.

Mutual information theory is used to determine the importance level of suppliers. The combination of importance and resilience provide a more holistic direction for future action: Identify those suppliers that are considered to be important to the operation of the manufacturer but that result in an increased probability of manufacturer disruption (i.e., suppliers that are less resilient). Changes in supplier selection could result, or the manufacturer can change contracts with existing important but less resilient suppliers such that they engage in more effective pre- and post-disruption planning.

Research Output

A conference paper was submitted to the 2018 Acquisition Research Symposium, but the abstract for the paper was not accepted for the conference. A journal article discussing the methodology and results of this report is being prepared for submission.

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