Risk and Failure Resilience of Interdependent Transportation Systems

Final Report
August 2018

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This study explores the gap between quantitative and qualitative assessment of engineering resilience in the domain of complex transportation infrastructure systems. A conceptual framework was developed for modeling engineering resilience, and then a Bayesian network was employed as a quantitative tool for the assessment and analysis of engineering resilience. A case study involving a transportation system for an aircraft manufacturing supply chain was employed to demonstrate the developed research and tools. The developed resilience quantification and analysis approach using Bayesian networks could empower system designers to have a better grasp of the weaknesses and strengths of their own systems against system disruptions induced by adverse failure events.</td></tr>
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RISK AND FAILURE RESILIENCE OF INTERDEPENDENT TRANSPORTATION SYSTEMS

Final Report
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EXECUTIVE SUMMARY

Complex interdependencies between critical infrastructure systems such as transportation infrastructures exacerbate the consequences of initial failure events through cascading failure effects and the propagation of damages. To address an increasing demand to develop highly resilient transportation infrastructure systems, the objective of this research was to create a Bayesian network (BN) based probabilistic platform for analysis and design that would enable interdependencies among the components and subsystems being considered, resilience realization through system design, and resilience restoration by optimized failure mitigation/recovery before or after major adverse events.

This study was motivated by the emerging need to develop high-reliability, low-cost, critical interdependent transportation infrastructure systems, in which not only reliable functions for each subsystem but also reliable dependencies across subsystems are required to maintain the desired functionality of the system when it faces system failures due to major natural disasters or gradual aging effects.

This research explores the gap between quantitative and qualitative assessment of engineering resilience in the domain of complex transportation infrastructure systems. A conceptual framework was first proposed for modeling engineering resilience, and then a Bayesian network was employed as a quantitative tool for the assessment and analysis of engineering resilience. A case study involving a transportation system for an aircraft manufacturing supply chain was employed to demonstrate the developed research and tools. The developed resilience quantification and analysis approach using Bayesian networks could empower system designers to have a better grasp of the weaknesses and strengths of their own systems against system disruptions induced by adverse failure events.

INTRODUCTION

With the development of complex engineering systems, such as power grids, transportation networks, nuclear power plants, spacecraft, healthcare delivery, and multi-level supply chain systems, new types of safety issues and unforeseen failure modes may arise. A traditional probabilistic risk assessment framework, which works well in the quantification and prevention of common system failure scenarios, falls short in evaluating the risks involved in the unexpected adverse failure events of complex engineering systems, such as major failures induced by natural disasters.

Currently, most engineering systems are designed with a passive and fixed design capacity in terms of the load level that the system is designed to withstand. To maintain the desired level of system reliability, a great deal of redundancy is typically designed into most engineering systems, which causes a strikingly high life cycle cost (LCC). For instance, the LCC of dual-redundant functions in an unmanned aerial vehicle (UAV) is about $97 million, whereas triple-redundant functions cost about $132 million (Malloy 2003). In addition to the high LCC, a high level of system redundancy also involves additional material usage and causes greater environmental impacts in manufacturing and operation processes.

The need for new design tools with greater functionality for developing high-reliability, low-cost, and sustainable engineering systems has reached a critical stage for two reasons: (1) an increase in system complexity poses a significant challenge for designers to take into account all potential failure modes that could occur during the operational stage of a system and (2) a growing trend in developing systems with a long useful life simultaneously challenges system designers in the early design stages to project the environmental usage impacts of the system, given evolving retrofitting events occurring at the same time. In facing the aforementioned challenges in developing complex engineering systems, the concept of resilience provides a new way to cope with system complexity and address system failures with a focus on failure prevention and recovery efforts.

Resilience implies the ability of a system to autonomously recover from or adjust easily to misfortune or change. Systems in nature have served as an inspiration for countless inventions and innovations. The ability of an ecosystem to return to its original state after being disturbed is an excellent example of resilience. It is conceivable that engineering design can significantly benefit from resilient activities in non-engineering fields in terms of addressing adverse failures and creating more resilient and sustainable engineering systems. Research on resilience has been widely conducted in recent years in many diverse areas, including ecosystem studies (Webb 2007, Kerkhoff and Enquist 2007), psychology (Pan and Chan 2007, Bonanno et al. 2005), enterprise studies (Wang et al. 2010), engineering (Titus 2006), and other areas, with the objective of improving the ability of a system or an individual/organization to withstand and recover rapidly from adverse failures. In the mechanical engineering domain, resilience is often defined as the ability of a material to return to its original shape following a deformation (e.g., being bent, pulled, stretched, or pressed) (Sheffi and Rice 2005, Bhandari 2010).

Many approaches have been proposed to model, assess, and improve resilience in various engineering areas. In the area of infrastructure systems, Cox et al. (2011) presented a set of operational metrics (vulnerability, flexibility, and resource availability) to estimate a transportation system's resilience when facing sudden attacks. Miller-Hooks et al. (2012) measured the resilience of freight transportation networks as the expected fraction demand that can be satisfied post-disaster. Shafieezadeh and Burden (2014) offered a probabilistic framework for a scenario-based resilience assessment of infrastructure systems; the authors defined resilience as the ratio of the areas in which the system responds well to hazards to the baseline system response during the same period. Omer et al. (2009) defined telecommunication cable system network resilience as the ratio of the value delivery of the network after a disruption to the value delivery before a disruption.

In the domain of cyber-physical systems, Cardenas et al. (2009) suggested resilience strategies that can be useful for designing control systems: redundancy, diversity, and limited privileges for corrupted entities. In container terminal operations, Pant et al. (2014) quantified resilience by applying a stochastic measure of resilience that included time to total system restoration, time to full system service resilience, and time to α–% resilience. Zobel and Khansa (2014) provided a quantitative measure of resilience in the presence of multiple related disaster events. Their predicted resilience was calculated based on the percentage of possible loss over a time interval. To assess supply chain resilience assessment, Spiegler et al. (2012) used an integral of time absolute error (ITAE) framework based on three attributes: readiness, responsiveness, and recovery. Youn et al. (2011a) proposed a resilience-driven system design framework for complex engineering systems that contains three hierarchical tasks: (1) the resilience allocation problem (RAP), (2) system reliability-based design optimization, and (3) system prognostics and health management (PHM) design. They showcased their proposed approach in the mechanical system design of an aircraft actuator. Li and Xi (2014) employed a quantitative resilience assessment on a computer numerical control (CNC) machining system based on engineering recoverability.

While most of the abovementioned research focused on analyzing engineering resilience from a qualitative standpoint, there is a significant gap in assessing engineering resilience through quantitative approaches. In addition, the quantitative resilience analysis tools that can be readily used by system designers to model and quantify engineering resilience are still underdeveloped. Therefore, this study proposes a quantitative resilience framework that defines resilience as a function of two essential attributes: reliability and restoration. A Bayesian network (BN) is then employed as an assessment tool to model and quantify engineering resilience in the presence of uncertainties, such as internal and external disruptions.

Possessing the unique feature of being able to combine graph theory with statistical theory, a Bayesian network offers several advantages in modeling complex systems with random variables. First, a Bayesian network displays causality among variables in a compact way through a directed acyclic graph (DAG). Given this characteristic, a Bayesian network is considered a good candidate to use for elicitation, in the sense of breaking down problems to lower-dimension sub-problems (Uusitalo 2007). Second, a Bayesian network allows for the combination of different data sources (Heckerman et al. 1995). Input data for Bayesian networks can be actual data (experimental, simulation, historical), expert knowledge, or a combination of both. Bayesian networks are very helpful in modeling a complex system when it is not feasible or practical to measure vital variables due to system constraints. Third, a Bayesian network is able to aid in the decision-making process due to its fast response in computing results (Stewart et al. 2014, Heckerman 1997). The advantages of Bayesian networks are not limited to the three points previously mentioned. Through its simple but powerful attributes, a Bayesian network can be readily adopted in modeling any complex system or real-world application that involves uncertainties. This study extends the practice of using a Bayesian network as an assessment tool to aid as a modeling foundation to develop more resilient engineering systems.

ENGINEERING RESILIENCE CONCEPTIONS

As discussed in the previous chapter, there has been considerable research conducted to develop the concept of resilience in non-engineering domains; however, the concept of resilience in the engineering domain remains a challenge, and there is an essential need to develop a generic framework to address resilience for engineering systems. This chapter provides a general framework that is widely applicable to engineering systems for the purpose of evaluating resilience.

Non-resilient engineering systems may gradually downgrade toward a low level of performance and capacity due to adverse disruptive events. In contrast, engineering systems with a high level of resiliency have the capability of robust recovery from an unhealthy state through the restoration of system capacity. To model resiliency for general engineered systems, four distinct states were defined:

1. Reliability state (SI): Baseline or original state, where the system operates normally
2. Vulnerability state (SII): Disrupted state caused by a disruptive event
3. Restoration state (SIII): State in which the system is restored as a result of a restoring effect
4. New steady state (SIV): A new steady state after the successful completion of the restoration state

These four states are related by the disruptive event (ei), as depicted in Figure 1.

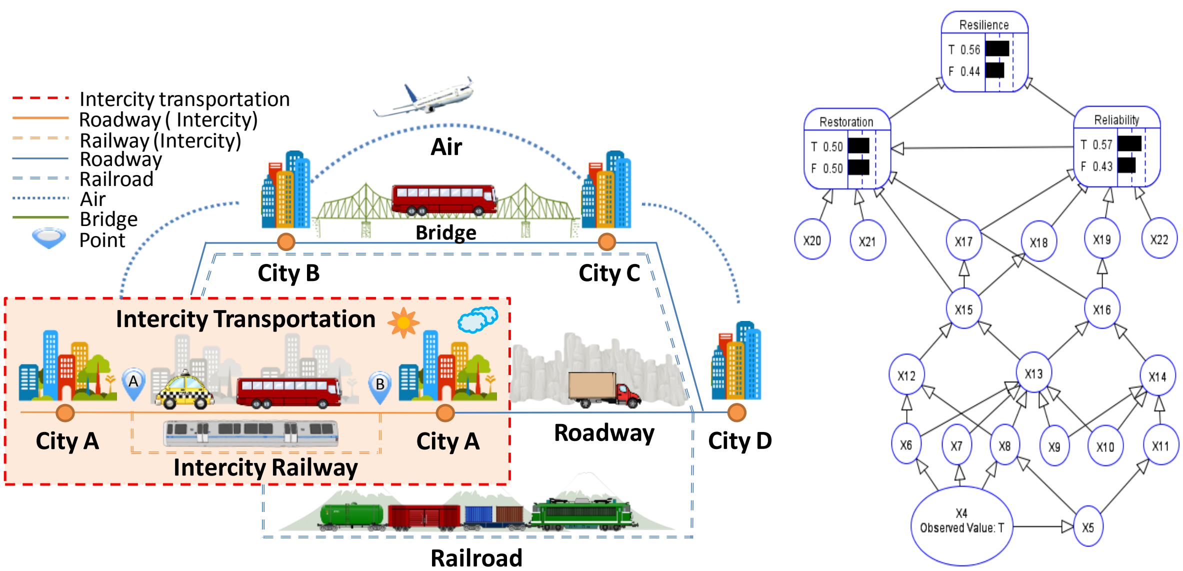
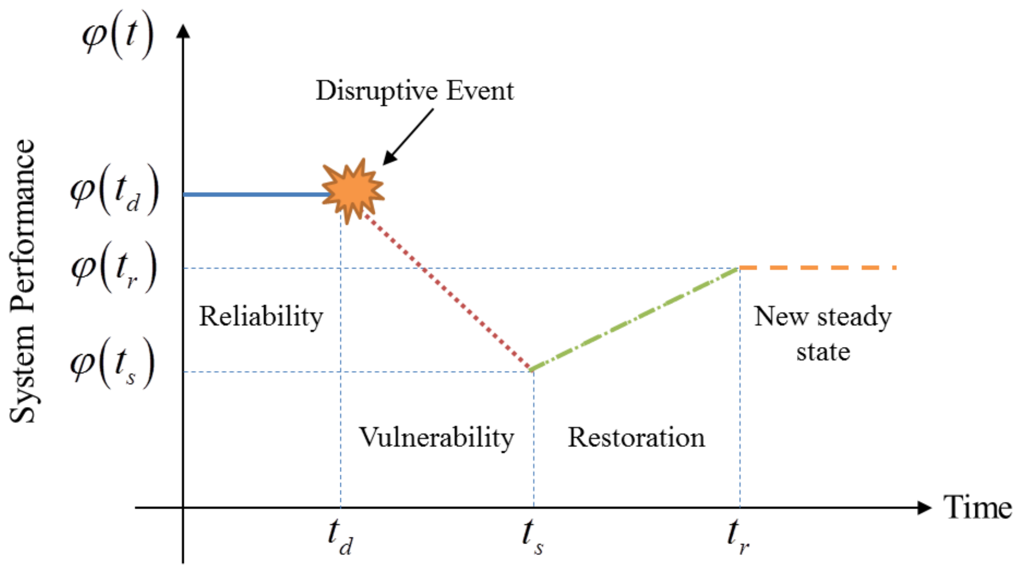


Figure 1. Interdependent transportation system infrastructure (left) and Bayesian network model for resilience modeling (right)

In the first state, reliability, the system operates under normal conditions until the disruptive event occurs at time (td). The second state, vulnerability, is described by the system performance function φ (e.g., capacity, inventory), which gradually downgrades from φ(td) to φ(ts) within time (td, ts) due to the occurrence of the disruptive event. The restoration state, which involves restoration from the disruption event, launches at time (ts) and ends at time (tr) and is described by the restoring system performance function (φ(tr) - φ(ts)). Lastly, the system reaches a new steady state at transition time (tr) and is described by the system performance function φ(tr). It should be noted that the system performance function at the new steady state φ(tr) is not necessarily equal to that at the reliability state φ(td). Depending on the restoration effect, φ(tr) could be lower or even higher than the state before the disruption event.

From Figure 2, it is clear that the magnitude of resilience is highly dependent on when and how the system capacity is restored.



From Yodo and Wang 2016, After Hosseini et al. 2014

Figure 2. Description of four transition states over time with respect to system performance function

In general, the restoration level can be defined as the degree of reliability recovery (Youn et al. 2011a, 2011b). The conceptual definition of resilience, as shown in Figure 2, can be quantified based on the probabilities of passive survival rate (reliability) and proactive survival rate (restoration) after the disruptive event, as expressed mathematically in Equation (1). In abstract algebra, ⊕ denotes the direct sum and ≜ means “is defined as” or “is equal to by definition.”

$$\text{Resilience } (\psi) = \text{Relaibility}(R) \oplus \text{Restoration}(\rho) \quad (1)$$

It should be noted that by deriving Equation (1), the engineering resilience can be measured quantitatively. Depending on the reliability and restoration strategies, both reliability and restoration can be derived as a set of conditional probabilities. Youn et al. (2011a) derived restoration as a conditional probability of a system failure event (1 - R), correct diagnosis event

(ΛD), correct prognosis event (ΛP), and mitigation/recovery action success effect (κ). Thus, resilience can also be written as Equation (2).

$$\psi = R \oplus \rho\left(R, \Lambda_P, \Lambda_D, \kappa\right) \tag{2}$$

FRAMEWORK FOR MODELING RESILIENCE BASED ON A BAYESIAN NETWORK

This chapter introduces a general framework that could be used to facilitate the modeling phase of engineering resilience. The framework is structured based on a Bayesian network approach. To do this, the BN is first presented in the next subsection, followed by a discussion on utilizing the Bayesian network to develop a general framework for engineering resilience.

Bayesian Network

A Bayesian network, also known as Bayes network or belief network, is a directed acyclic graph that aims to represent the probability properties among variables of interest in an uncertain-reasoning problem (Heckerman et al. 1995, Stewart et al. 2014). In other words, a Bayesian network is able to graphically represent relationships between variables in complex systems in a natural and compact way, which makes BN suitable for modeling many real-world applications: forecasting (Sun et al. 2006), data mining (Shetty et al. 2007), risk assessment (Weber et al. 2012), and many other applications that involve complex systems.

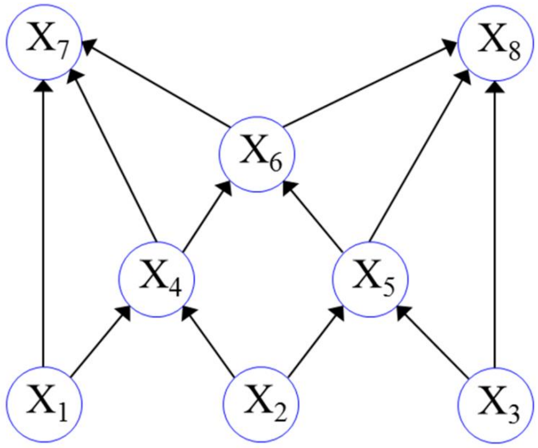
The Bayesian network approach can be understood as follows. A BN can be represented as G = (V, E), where a graph (G) is a collection of a set of vertices (variables or nodes) $V = \{X_1, X_2, \ldots, X_n\}$ and a set of edges (arcs or links) represented by (E). A link from node X_i to X_j indicates a causal relation between these two vertices, in which the value of X_j is dependent on the value of X_i. Here, X_i is called the parent of X_j, or X_j is the child of X_i. A vertex without any parent is called a root vertex, and a vertex without any child is called a leaf vertex.

In Bayesian networks, the dependency relationships among variables $V = \{X_1, X_2, \ldots, X_n\}$ are quantified by conditional probability distributions. Let $pa(X_i)$ be a set of all parents of variable X_i. The conditional probability distribution attached to variable X_i is represented as $P(X_i|pa(X_i))$. The joint probability distribution of all variables specified in (V) can be constructed from conditional probability distributions, as shown mathematically in Equation (3).

$$P\left(X_1, X_2, ..., X_n\right) = P\left(X_1 | pa(X_1)\right) \cdot P\left(X_2 | pa(X_2)\right) ... P\left(X_n | pa(X_n)\right)$$

$$P\left(X_1, X_2, ..., X_n\right) = \prod_{i=1}^{n} P\left(X_i | pa(X_i)\right) \tag{3}$$

Bayesian networks require fewer parameters than the conventional method because only parameters of interest are taken into consideration. This is a key advantage of the Bayesian network approach. An example BN with eight variables is depicted in Figure 3.



Hosseini et al. 2014

Figure 3. Sample Bayesian network with eight variables

The corresponding decomposition of the joint probability distribution of the variables is given by the following:

$$
\begin{aligned}
P(X_1,\cdots,X_8) = {} & P(X_1)\cdot P(X_2)\cdot P(X_3) \\
& \cdot P(X_4 \mid X_1, X_2)\cdot P(X_5 \mid X_2, X_3)\cdot P(X_6 \mid X_4, X_5) \\
& \cdot P(X_7 \mid X_1, X_4, X_6)\cdot P(X_8 \mid X_3, X_5, X_6)
\end{aligned}
\tag{4}
$$

To calculate the joint distribution of eight variables, unconditional distributions of $P(X_1)$, $P(X_2)$, and $P(X_3)$ and the conditional probability of $P(X_4| X_1, X_2)$, $P(X_5| X_2, X_3)$, $P(X_6| X_4, X_5)$, $P(X_7| X_1, X_4, X_6)$, and $P(X_8| X_3, X_5, X_6)$ must be determined. Conditional probability can be obtained from conditional probability tables (CPTs). These tables may be directly measured, learned from data, determined by expert knowledge, or obtained from a combination of prior or expert knowledge and data (Heckerman and Breese 1996). As illustrated in the previous example, Bayesian networks are capable of modeling joint probability distributions in a compact and economical manner.

One beneficial property of a Bayesian network is known as belief propagation, which enables decision makers to update the probabilities of variables $P(X_i)$ after observing the values of those variables. This observed information is then called evidence and is denoted by (e). For instance, in Figure 3, some evidence has been observed in variable X_5. In this case, the conditional probability distribution of variable X_5 was given the value of all variables except X_5, where $X_5 = \left(e = \{X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8\}\right)$, and is calculated as follows:

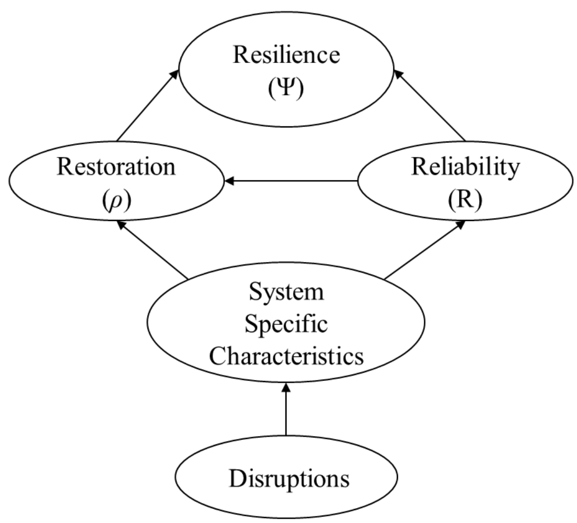
$$
P(X_5 \mid e) = \frac{P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8)}{\sum_{X_5} P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8)} \tag{5}
$$

This conditional probability can be reformulated as follows:

$$P(X_5 \mid e) = \frac{P(X_5 \mid X_2, X_3)P(X_6 \mid X_4, X_5)P(X_8 \mid X_3, X_5, X_6)}{\sum_{X_5} P(X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8)} \tag{6}$$

Resilience Assessment

This section presents a generic framework for modeling the engineering resilience of complex systems based on a Bayesian network. A general schematic of the described framework is depicted as a DAG in Figure 4.



After Hosseini et al. 2014

Figure 4. Conceptual scheme of resilience for engineering systems

As mentioned in the previous section, there are two important system attributes in assessing resilience in complex engineering systems: reliability and restoration. As seen in Figure 4, both reliability and restoration serve as prior nodes to the top resilience node.

A downgraded system only occurs when there are failures observed in the system, so, in other words, when reliability fails. There is a need for a downgraded system to be restored to an optimal operating condition after the occurrence of a disruptive event. The probability of system's restoration depends on the probability of system reliability in the pre-disturbance state and the probability of system characteristics being downgraded due to disruptions. Thus, the reliability node and system-specific characteristic nodes serve as prior nodes to the restoration node. System-specific characteristic nodes tend to include the difference of specific system applications using the proposed framework. Such characteristics include the system's structures, the logic connections of the subsystems, and interactions of the system with the environment. To develop a general framework for resilience analysis, the researchers used the term "system-specific characteristic" to represent the Bayesian network representation of a system, and, further, reliability and restoration of the system depend largely on system-specific characteristics.

In addition to system restoration, system characteristics also determine the reliability level of the system. The Bayesian network approach has been employed in reliability analysis for complex systems by various researchers (Torres-Toledano and Sucar 1998, Bobbio et al. 2001, Boudali and Dugan 2005). The reliability of the system can be obtained using probability propagation techniques after the reliability system structure has been transformed into a Bayesian network representation using reliability block diagrams (RBDs) or fault trees (FTs) (Torres-Toledano and Sucar 1998). RBDs and FTs are graphical methods that show how interactions among components or subsystems contribute to system reliability. Similar to RBDs or FTs, system-specific characteristic nodes consist of many interconnected specific sub-nodes that are essential in defining reliability and restoration measures in the system. System-specific characteristic nodes tend to include the difference of specific system applications using the proposed framework. Such characteristics include the structures of the system, the hierarchy and logic connections of the subsystems, and interactions of the system with the environment.

Without loss of generality, two types of disruptions were considered in this study: internal disruptions (human error, component failure, etc.) and external disruptions (earthquake, hurricane, etc.). These are considered to be the main root causes of all disruptive events that are likely to happen. Upon perception of disruptions (external and/or internal), system characteristics such as capacity or inventory may gradually downgrade over time. It is clear that the probability of failure of a system's characteristics can be expressed in terms of the probability of occurrence of internal and external disruptions.

In the Bayesian network structure of this resilience assessment, internal and external disruptions are the root nodes, and system resilience is the leaf node. The probability of system resilience is expressed as a function of the probability of system reliability and the probability of system restoration. By incorporating the Bayesian network approach, the joint probability distribution of engineering resilience can be represented by Equation (7). Since the resilience node in the Bayesian network is defined as the probability of success in achieving resilience in the complex system, this node takes a value between 0 and 1.

$$\begin{aligned}\text{Resilience} = {} & P\,(\text{Disruptions}) \\ & \cdot P\,(\text{System Specific Characteristics} \mid \text{Disruptions}) \\ & \cdot P\,(\text{Reliability} \mid \text{System Specific Characteristics}) \\ & \cdot P\,(\text{Restoration} \mid \text{Reliability, System Specific Characteristics}) \\ & \cdot P\,(\text{Resilience} \mid \text{Reliability, Restoration})\end{aligned} \tag{7}$$

CASE STUDY

Electric Motor Supply Chain

In this case study, the resilience of an electric motor supply chain was examined. This case study was chosen for the following reasons: (1) a supply chain system is considered a complex system, in that a typical supply chain consists of different tiers of suppliers that are interconnected with each other, and (2) disruptions to supply chain systems may have adverse impacts on financial conditions and the operations of suppliers, manufacturers, and stakeholders.

In 2011, a massive earthquake with an 8.9 magnitude struck the northeast coast of Japan, followed by a tsunami and nuclear accidents. This devastating disaster resulted in the most costly natural disaster in Japan's modern history (Park et al. 2013). A number of manufacturing facilities specializing in specialty paint, semiconductors, and other automobile parts, which are essential to the global motor vehicle supply chain, were adversely affected by this disaster and temporarily shut down (Canis 2011, Nanto et al. 2011). Worldwide automakers, including Ford, Chrysler, Volkswagen, BMW, Toyota, Honda, and GM, suffered from a parts shortage, which resulted in lower production output and excessive loss. For several weeks after the disaster, according to Canis (2011), a shortage of over 150 parts left Toyota's North American operations operating at 30% capacity. The total loss from this natural disaster was estimated to be around $300 billion (Canis 2011, Nanto et al. 2011). This indicates that disruptions to supply chains can cause a huge negative impact on the performance of manufacturers, suppliers, and market conditions. Therefore, it is incumbent to investigate the role of resilience in supply chain systems.

Case Study Description

The electric motor supply chain case study being investigated is a three-tier supply chain that involves the following: suppliers, manufacturers, and distribution centers. An electric motor is composed of two assembly parts: a drive assembly and a case assembly. The drive assembly is made by assembling a rotor and stator together, while the case assembly is made by assembling a shield and base together. The main parts of a motor and its assembly structure are shown in Figures 5 and 6, respectively.

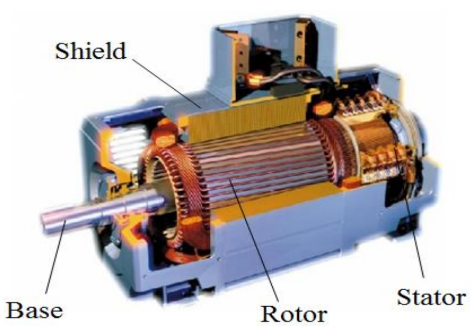


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Figure 5. Main parts of electric motor

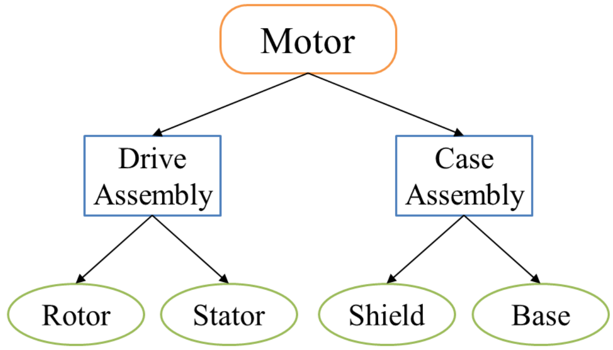

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Figure 6. Assembly structure of electric motor

Components of the supply chain, along with their locations, are illustrated in Figure 7.

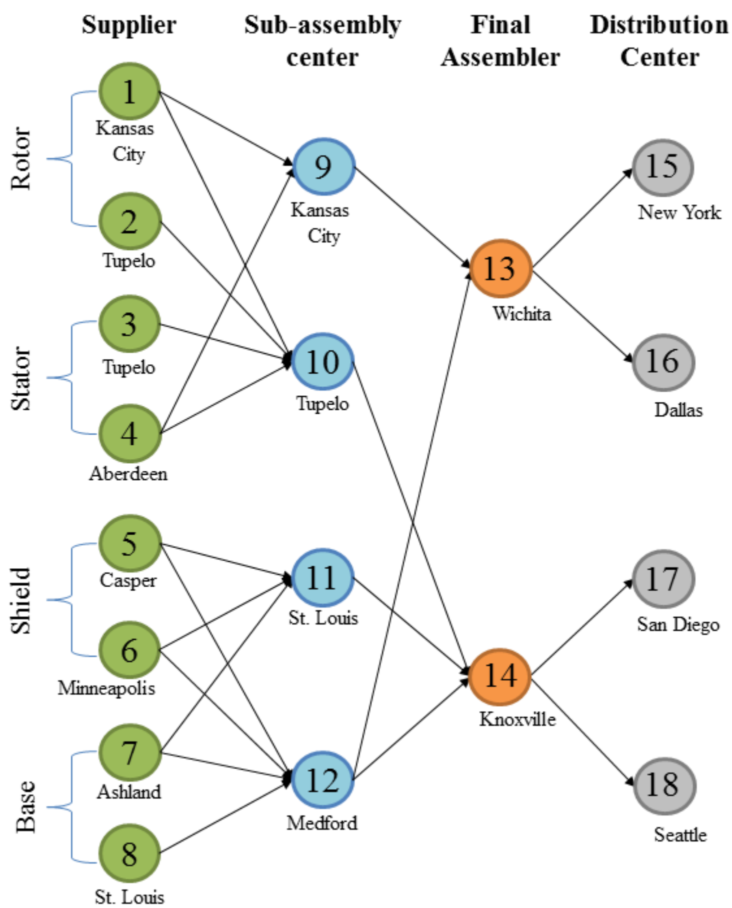

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Figure 7. Supply chain network of electric motor

This supply chain has eight suppliers, where suppliers (1, 2), (3, 4), (5, 6), and (7, 8) are committed to supplying the rotor, stator, shield, and base, respectively, to the sub-assembly manufacturers. There are four sub-assemblers: sub-assemblers (9, 10) are dedicated to making the drive assembly by assembling the rotor and stator, and sub-assemblers (11, 12) are committed to making the case assembly by assembling the shield and base. The drive and case assemblies are further assembled to make the electric motor at two final assembly locations (13&14). The electric motors are then distributed to four distribution centers (15, 16, 17, and 18).

The Bayesian network for assessing the resilience of the electric motor's supply chain is structured through historical data and knowledge from subject matter experts. The proposed structured Bayesian network is shown in Figure 8.

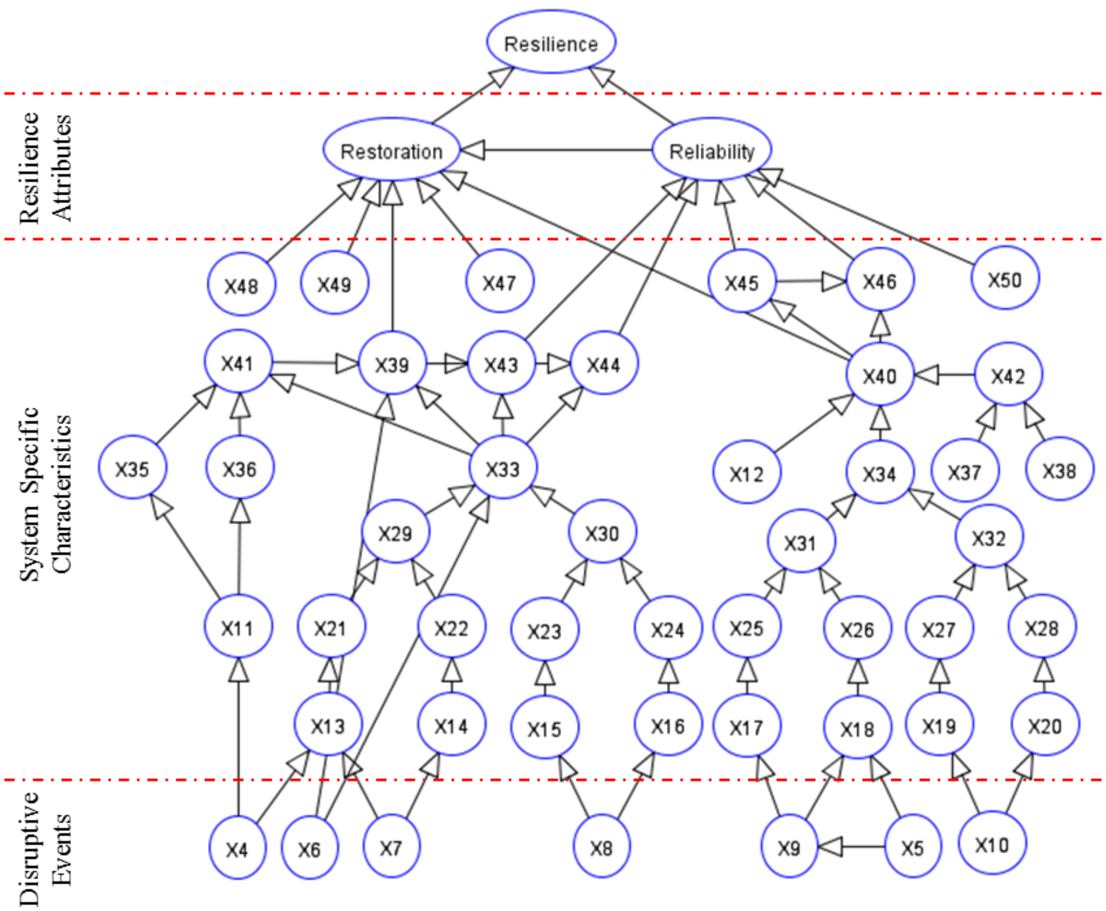

Figure 8. Bayesian network for electric motor supply chain

The causal relationships between the components in the electric motor supply chain were obtained using the belief propagation of suppliers and manufacturing experts. A list of components involved in modeling the resilience of the supply chain is tabulated in Table 1.

Table 1. List of variables used in modeling supply chain resilience

Node	Variable
	Resilience Attributes
X1	Supply chain's resilience
X2	Supply chain's reliability
X3	Supply chain's restoration
	External Disruptive Events
X4	Flood
X5	Hurricane
X6	Tornado
X7	Fluctuation of rotor price
X8	Fluctuation of stator price
X9	Fluctuation of shield price
X10	Fluctuation of base price
	Internal Disruptive Events
X11	Transportation failures
X12	Machine breakdowns
	System-Specific Characteristics
X13	Capacity of rotor's supplier (Kansas City)
X14	Capacity of rotor's supplier (Tupelo)
X15	Capacity of stator's supplier (Tupelo)
X16	Capacity of stator's supplier (Aberdeen)
X17	Capacity of shield's supplier (Casper)
X18	Capacity of shield's supplier (Minneapolis)
X19	Capacity of base's supplier (Ashland)
X20	Capacity of base's supplier (St. Louis)
X21	Lead time of rotor's supplier (Kansas City)
X22	Lead time of rotor's supplier (Tupelo)
X23	Lead time of stator's supplier (Tupelo)
X24	Lead time of stator's supplier (Aberdeen)
X25	Lead time of shield's supplier (Casper)
X26	Lead time of shield's supplier (Minneapolis)
X27	Lead time of base's supplier (Ashland)
X28	Lead time of base's supplier (St. Louis)
X29	Lead time of drive assembler (Kansas City)
X30	Lead time of drive assembler (Tupelo)
X31	Lead time of case assembler (St. Louis)
X32	Lead time of case assembler (Medford)
X33	Lead time of motor manufacturer (Wichita)
X34	Lead time of motor manufacturer (Knoxville)
X35	Inventory of drive assembler (Kansas City)
X36	Inventory of drive assembler (Tupelo)
X37	Inventory of case assembler (St. Louis)
X38	Inventory of case assembler (Medford)
X39	Performance of motor manufacturer (Wichita)
X40	Performance of motor manufacturer (Knoxville)

Node	Variable
X41	Safety stock of manufacturer (Wichita)
X42	Safety stock of manufacturer (Knoxville)
X43	Service level of distribution center (New York)
X44	Service level of distribution center (Dallas)
X45	Service level of distribution center (San Diego)
X46	Service level of distribution center (Seattle)
X47	Stand-by supplier for rotor
X48	Stand-by supplier for shield
X49	Alternative transportation
X50	Suppliers' quality ratings

Through investigation of historical data and several questionnaires completed by suppliers, manufacturers, and distribution managers, it was found that the three types of natural disasters that are most likely to affect the electric motor supply chain are flood, hurricane, and tornado. These natural disasters can adversely impact the capacity of the rotor supplier in Kansas City (X13), the capacity of the shield supplier in Minneapolis (X18), and the lead time of the final assembler in Wichita (X33). It was also found that price fluctuations for the rotor, stator, shield, and base in markets (X7–X10) can have a negative influence on the capacities of their corresponding suppliers. Insufficient supplier capacities will result in extended supplier lead time (X21–X28). The lead times of the drive and case sub-assemblers (X29–X32) are directly dependent on the lead times of their corresponding suppliers; similarly, the lead times of the final assemblers (X33, X34) are related to the lead times of the drive and case assemblers, so these causalities are important considerations when modeling a supply chain's resilience. The performance of motor manufacturers (X39, X40) can be expressed as a function of their lead times and safety stocks. Therefore, the lead times and safety stocks of manufacturers are displayed as children of a manufacturer's performance. Performance of the final assembler also serves as an index to assess the service level of distribution centers (X43–X46). In the Bayesian network resilience model, service levels in different locations are considered the parents of the final assembler performance variables.

The overall electric motor supply chain's reliability (X2) is defined as a function of the distribution centers' service levels (X43–X46) and the suppliers' quality ratings (X50). Therefore, the probability of failure in system reliability is dependent on the probability of the failure of its attachments. The suppliers' quality ratings provide a dimension of input for the ratings of the quality of different suppliers, which could be quantified, for example, from the rejection rate of incoming parts from lower-tier suppliers. To define causality in the restoration node (X3), variables that may have a direct impact on restoration actions should be identified. The first variable is redundancy (i.e., having stand-by suppliers for critical parts such as rotors and shields (X47, X48) or alternative transportation resources (X49)). These strategies could improve the system's restoration by substituting failed-to-perform suppliers with stand-by suppliers. The second variable is the performance of the motor manufacturer (X39, X40). Systems with excellent performance are more likely to be restored rapidly with minimal effort. The reliability of the supply chain system (X2) is the third variable in the restoration node because systems with a higher degree of reliability are less prone to disturbances. Finally, the resilience variable (X1) is defined as a function of the reliability (X2) and restoration (X3) variables, as pre-defined (see Equation (1)). In this case study, the resilience node is the leaf node.

Bayesian Network for Resilience Analysis

A schematic of the Bayesian network structure for the proposed models is presented in Figure 8. All variables in the electric motor supply chain case study are modeled in two states: failure state or success state. For example, a success state for the lead time of the motor manufacturer in Wichita (X33) means that the manufacturers are able to supply the product on time (no delay) to the designated distribution centers, while a failure state is used when the manufacturer fails to supply the product on time to the distribution centers. After constructing the graphical network, the next step is to determine all the conditional and unconditional (prior) probabilities. The probabilities in this model reflect the decision maker's belief regarding the likelihood of the occurrence of events. The links between each of the nodes represent the dependencies among the variables.

Since all variables are discrete, the conditional probability distributions are represented in a CPT. For example, Figure 9 shows the relationship between flood (X4), rotor price fluctuation (X7), and the supplier's capacity in Kansas City (X13). The conditional probability of node X13 is dependent on the prior probabilities of X4 and X7. Subject matter experts need to determine the first four of the eight possible combinations of events that are likely to happen, and the following four combinations are complementary to the first four.

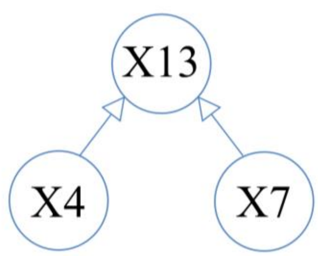

Figure 9. Relationship between nodes X4, X7, and X13

In Table 2, nodes with state F (False) are in a success state, while nodes with state T (True) have failed to succeed. For example, the third row represents the conditional probability of failure for node X13, given the failure of node X4 and the success of node X7. The other CPTs are not discussed in this report. Note that the conditional probabilities of all states are calculated using a mix of beliefs, expert knowledge, and historical data.

Table 2. Conditional probability table (X13 | X4, X7)

Row	X4	X7	X13	Probability
1	F	F	F	0.95
2	F	T	F	0.8
3	T	F	T	0.4
4	T	T	T	0.65
5	F	F	T	0.05
6	F	T	T	0.2
7	T	F	F	0.6
8	T	T	F	0.35

* T = True, failure state, F= False, success state

In this case study, the managerial committee suspected that the final assemblers played an important role in the overall supply chain's resilience. Therefore, several scenarios that involved the performance and lead time of the final assemblers in Wichita and Knoxville were examined. There were 16 possible scenarios that could impact the resilience of the electric motor supply chain, and the results are shown in Table 3. X33 and X34 are the lead time of final assemblers in Wichita and Knoxville, respectively. Similarly, X39 and X40 correspond to the performance of the final assemblers in Wichita and Knoxville.

Table 3. Scenarios involving final assemblers in quantifying overall supply chain resilience

Scenario	X33	X34	X39	X40	Restoration	Reliability	Resilience	Failure Events
1.	F	F	F	F	0.89	0.84	0.86	None
2.	***T***	F	F	F	0.83	***0.48***	*0.65*	One
3.	F	T	F	F	0.89	0.84	0.86	
4.	F	F	T	F	0.71	0.60	0.66	
5.	F	F	F	***T***	0.70	***0.49***	***0.60***	
6.	T	T	F	F	0.83	0.65	0.48	Two
7.	F	F	***T***	***T***	0.51	0.36	***0.44***	
8.	T	F	T	F	0.67	0.39	0.53	
9.	F	T	F	T	0.70	0.49	0.60	
10.	***T***	F	F	***T***	0.68	0.30	***0.49***	
11.	F	T	T	F	0.71	0.66	0.60	
12.	T	T	T	F	0.67	0.39	0.53	Three
13.	T	T	F	T	0.68	0.30	0.49	
14.	T	***F***	T	T	0.49	0.26	***0.38***	
15.	F	T	T	T	0.51	0.36	0.44	
16.	T	***T***	T	T	0.49	0.26	***0.38***	Four

* T = True, failure state, F= False, success state

Scenario 1 is the original state of the electric supply motor chain, where there are no failures observed for any lead time or performance measures of the final assemblers. The original state indicates that the electric motor supply chain is 86% resilient. In other words, when the supply chain is functioning normally, without any disruptive events, it has an 86% success rate in achieving resilience. Scenario 2 through Scenario 5 show one disruptive event in the supply chain. Comparing these four scenarios, it can be seen that when one disruptive event happens at either node X33 (Scenario 2) or X40 (Scenario 4), the supply chain's resilience is greatly affected in terms of low supply chain reliability.

One may suspect that if X33 and X40 happen to fail at the same time (Scenario 10), this combination would result in the worst resilience value. However, this is not always the case. Comparing Scenario 6 through Scenario 11, where there are two failure events observed at the same time, Figure 10 shows that Scenario 7 has the lowest resilience (44%) instead of Scenario 11. This is because the interactions between the nodes in quantifying resilience in Scenario 7 are stronger compared to the interactions between the nodes in Scenario 10. In Scenario 7, the observed failure events are the performance of the final assemblers in Wichita (X39) and Knoxville (X40).

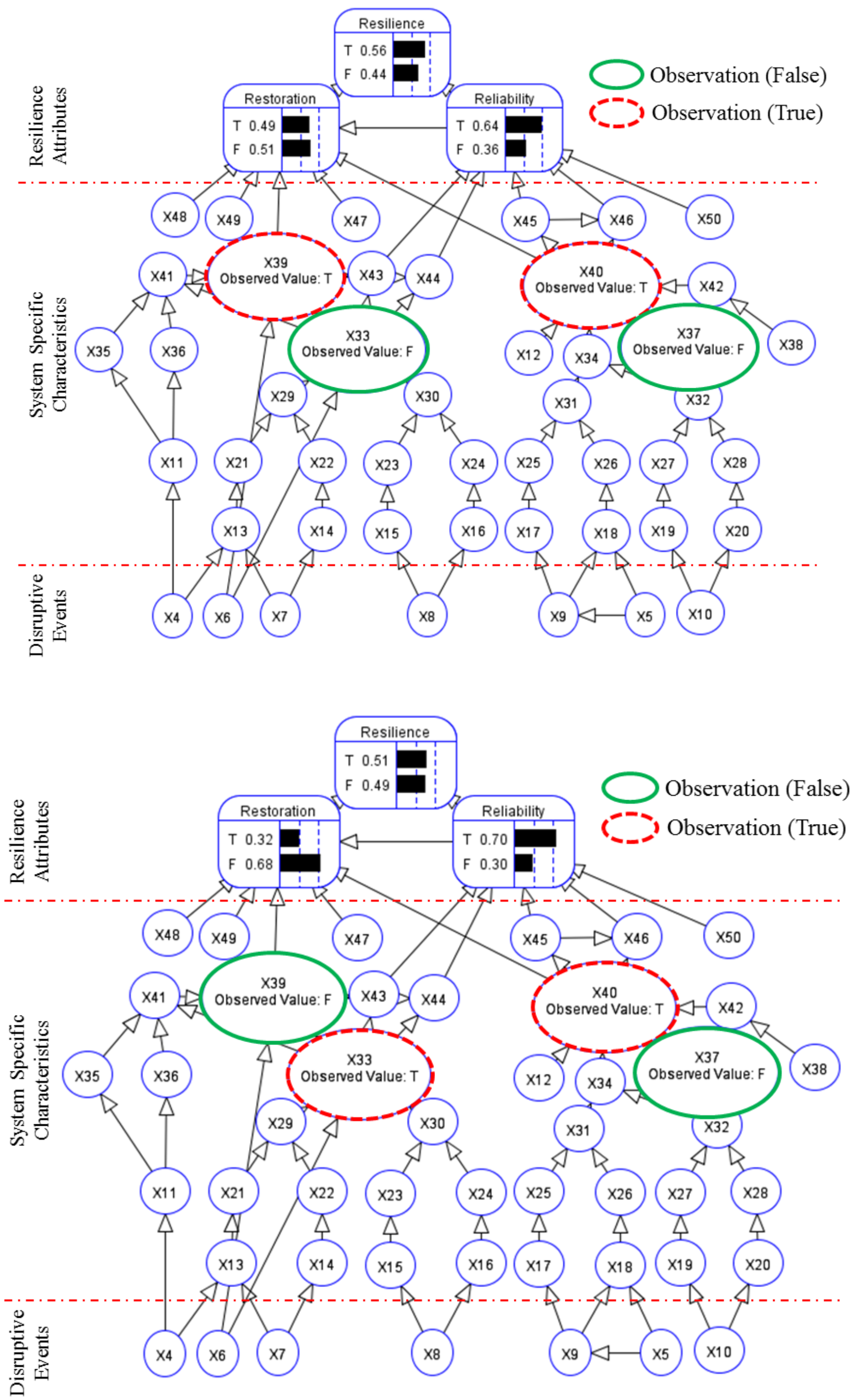

Figure 10. Comparison between Scenario 7 (top) and Scenario 10 (bottom) in resilience quantification

Likewise, Figure 11 indicates that Scenario 14 and Scenario 16 have the same resilience value of 38%, although there are three failure events observed in Scenario 14 and four failure events in Scenario 16. It can be concluded that X34 (lead time in Knoxville) does not have a great influence in the overall supply chain's resilience quantification. It should be noted that in this example, the results shown are the resilience values at different time instants, whereas resilience is time dependent and evolves over time.

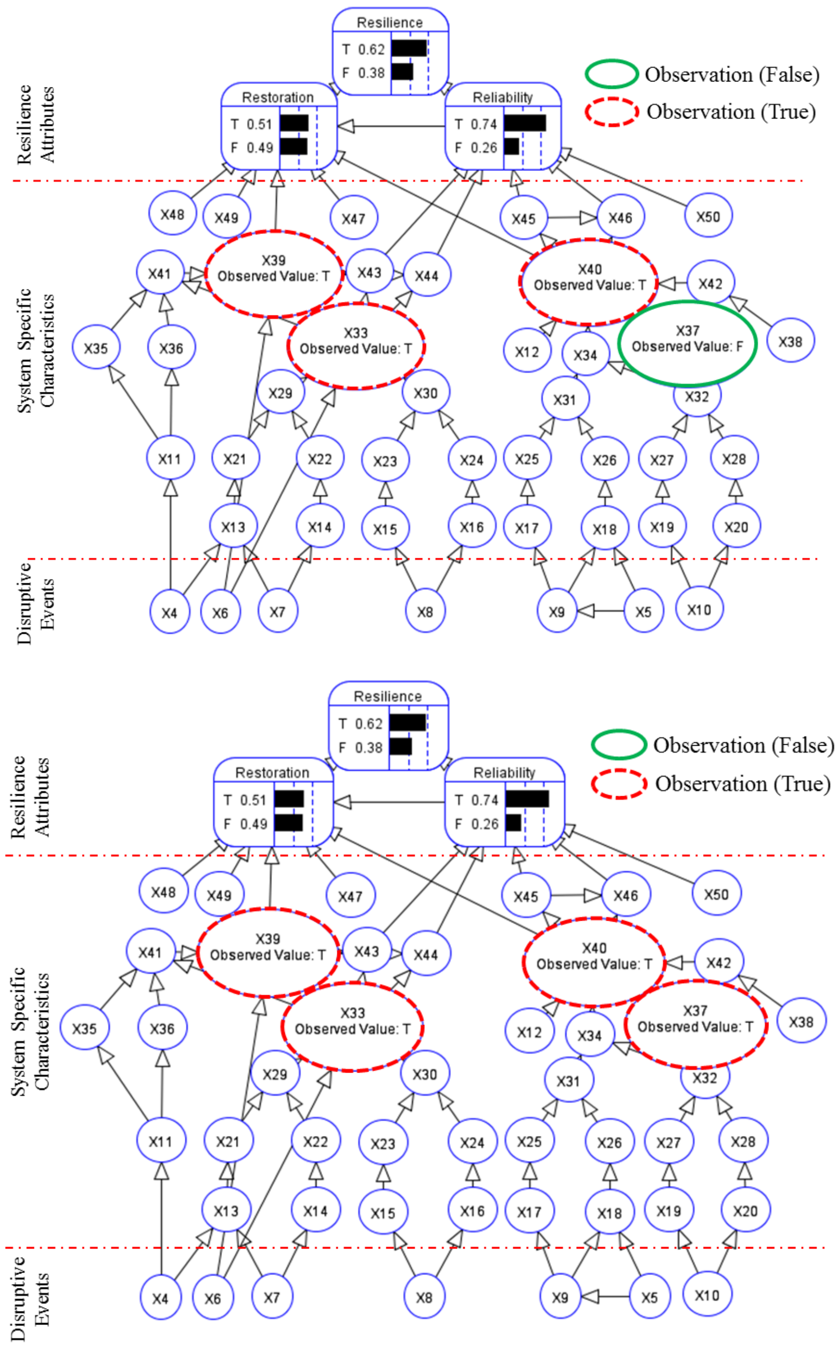

Figure 11. Comparison between Scenario 14 (top) and Scenario 16 (bottom) in resilience quantification

Compared to other models, a Bayesian network offers decision makers fuller insights into different scenarios that are likely to occur and provides these insights in a compact way. The ability of Bayesian networks to capture the strength of the causality between nodes can give decision makers a better understanding of the effects of the interactions among failure events in quantifying resilience. The dependencies among nodes may be critical in determining a system's resilience and should not be neglected. In terms of improving resilience, decision makers will be able to develop a better approach for budgeting when the dependencies among nodes are considered.

Discussion

In recent years, resilience concepts that describe the ability of a system to withstand failures and recover rapidly from adverse events have started to gain recognition in the field of engineering. In order for resilience concepts to be more applicable and useful to various engineering domains, one has to be able to measure resilience. However, readily used resilience quantification tools are still not well-developed. Therefore, this study proposes a Bayesian network as an assessment tool to model and quantify resilience.

The Bayesian network approach offers a simple and compact way of representing a complex system's resilience from different data domains. Using simple arcs and nodes, a BN graphically displays natural causal relationships among variables that are involved in molding a system's resilience. Statistically, the strength of the dependencies among variables can be measured by their conditional probabilities. A simple BN graph displays compact information in its nodes and arcs. As discussed in the previous section, three nodes and two arcs are able to represent the likelihood of eight different scenarios.

In addition to being simple yet compact, constructing a resilience model using a Bayesian network does not depend on the number of available data points. A BN takes into account all data and does not require minimum sample sizes when performing an analysis (Uusitalo 2007). The case study used in this research shows a resilience model of an electric motor supply chain constructed with 50 variables. It was able to demonstrate the effectiveness of the Bayesian network approach in modeling system resilience.

When modeling resilience, many interconnected variables influence the measure of resilience in a complex system. The input data for each component may not always be possible to obtain from only one data source. Therefore, allowing a combination of various data sources is a significant benefit of a Bayesian network in quantifying resilience in cases where some data may be missing, incomplete, or not able to be measured in real-time. Additionally, the variables and probabilities for restoration measures can be obtained from input by manufacturing experts.

Once the resilience model is constructed, the Bayesian network provides a fast response in evaluating the different possible scenarios. This unique attribute makes a BN a good tool to aid in decision-making, where quick responses are critical. Equipped with the advantage of being able to represent resilience statistically in a compact causal graph, a Bayesian network allows a transparent approach for decision makers to study and evaluate different resilience scenarios.

This is especially true on the occasions when dependencies between variables are critical, as demonstrated in the case study of the electric motor supply chain, where the dependencies among variables could be easily overlooked. Through the Bayesian network approach, a resilience concept can be realized and used to build low-cost, high-reliability, and sustainable complex systems.

Although a Bayesian network offers many benefits, there are some shortcomings. One of those is that a BN does not offer a feedback loop. Thus, updating a large Bayesian network may require a substantial amount of effort. To accommodate changes to the design of a system, a dynamic configuration for a BN must be considered. Considering the fact that resilience evolves over time, a dynamic Bayesian network (DBN) could be implemented to overcome the shortcomings of a BN. Although a Bayesian network is generally independent of the data mining process, it is considered a data-intensive and computationally expensive approach. Identifying important components that could be used to simplify the data required to build a Bayesian network is critical. Sensitivity analysis could be used in prioritizing critical components in the complex system. In addition, efficient computational algorithms could be sought to improve the efficiency of the proposed resilience modeling framework. Moreover, it is also important to note that the resilience level of a system is also determined by the resilience level of its components. Hence, optimizing the resilience level of the components is critical in defining the overall system's resilience. Future work in this area will be directed toward quantifying and optimizing resilience at the component level with the hope of being able to develop a more effective and readily used modeling tool that is not only dedicated to modeling but is also able to quantify engineering resilience in complex systems.

In this study, a Bayesian network has been proposed as an approach to modeling and quantifying resilience in complex engineering systems. The proposed framework can be used to facilitate the design of resilient engineering systems. As resilience is quantified with two essential attributes (reliability and restoration), improved designs of a system could be sought to improve the reliability of the system's components and subsystems as well as to employ more cost-effective restoration strategies. Although improving resilience for complex engineering systems is beyond the scope of this study, there are several resilience strategies that have been proposed by researchers in diverse engineering fields. Miller-Hooks et al. (2012) proposed maximizing the resilience of freight transportation networks through optimal allocation of a limited budget by focusing on preparedness and recovery activities. Omer (2013) suggested several resilience-enabling schemes to improve resilience by reducing vulnerability and increasing adaptive capacity.

PROJECT RESULTS AND ACCOMPLISHMENTS

Results and Conclusions

A general framework for the resilience of engineering systems was developed based on a Bayesian network. The framework was structured based on the relationship between system resilience, reliability, and restoration. To measure resilience in complex systems quantitatively under disruptive events, a Bayesian network was adopted. Employing a Bayesian network approach offers a high potential for successfully presenting ambiguous knowledge and performing reasoning under uncertainty. Another advantage of a BN is its causal representation of system characteristics. Bayesian networks relate system variables to each other by causal representation in a graph, thereby giving more transparent reasoning. A BN is constructed using a mix of sources, including historical data and expert knowledge.

The proposed approach was implemented through an assessment of resilience in an electric motor supply chain system. Different possible scenarios under different disruptive events were investigated to find the root cause of low resilience values. The Bayesian network aided in providing decision makers with visual and analytical insights into the variables that contribute to overall system resilience. Thus, improvement actions could be planned and executed correspondingly with the aim of building a more resilient complex engineering system.

Opportunity for Training and Development

The researchers have been incorporating the research findings into graduate courses at Wichita State University and other training events as follows:

- The principal investigator (PI) has incorporated the concepts of risk and resilience into the course IME-864: Risk Analysis, through projects dedicated to transportation system risk and resilience modeling and analysis.
- The PI has provided training seminars to a broader range of students and professionals through the IME colloquium, attended by graduate students from the College of Engineering at Wichita State University, local industrial professionals through the Wichita chapter of the Institute of Industrial and Systems Engineers (IISE), and local industrial advisory board members.
- The PI has also shared the results of this research at invited seminars at Argonne National Laboratory and Kansas State University.

Dissemination of Results

The researchers have actively disseminated the research results through presenting papers to relevant technical conferences, such as the International Design Engineering Technical Conferences & Computers and Information in Engineering Conference (IDETC/CIE).

Meanwhile, the researchers have made efforts to disseminate research results through collaborations with industry and national laboratories. Specifically, the researchers have been working with a leading electronics testing company (Integra Technologies, LLC) and national laboratory (NASA Ames Research Center) to develop research collaborations and disseminate research results.

The researchers have also established an industrial collaboration with Medtronic to disseminate research results through seminars while also obtaining internship opportunities for graduate students.

Products

Following are other papers based on the results of this study:

- Hosseini, S., N. Yodo, and P. Wang. 2014. Resilience Modeling and Quantification for Design of Complex Engineered Systems Using Bayesian Networks. *Proceedings of the ASME 2014 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference* (IDETC/CIE), Buffalo, NY, August 17–20.
- Yodo, N. and P. Wang. 2015. Resilience Analysis and Allocation for Complex Systems Using Bayesian Network. *Proceedings of the ASME 2015 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference* (IDETC/CIE), Boston, MA, August 2–5.
- Yodo, N. and P. Wang. 2016. Resilience Modeling and Quantification for Engineered Systems Using Bayesian Networks. *Journal of Mechanical Design*, Vol. 138, No. 3.
- Yodo, N. and P. Wang. 2016. Resilience Analysis for Complex Supply Chain Systems Using Bayesian Networks. 54th AIAA Aerospace Sciences Meeting, AIAA Science and Technology (SciTech) Forum and Exposition, San Diego, CA, January 4–8.
- Yodo, N. and P. Wang. 2016. Resilience Allocation for Early State Design of Complex Engineered Systems. *Journal of Mechanical Design*, Vol. 138, No. 9.
- Yodo, N. and P. Wang. 2016. Engineering Resilience Quantification and System Design Implications: A Literature Survey. *Journal of Mechanical Design*, Vol. 138, No. 11.
- Yodo, N., P. Wang, and Z. Zhou. 2016. Predictive Resilience Analysis of Complex Systems Using Dynamic Bayesian Networks. *IEEE Transactions on Reliability*, Vol. 66, No. 3, pp. 761–770.
- Yodo, N., P. Wang, and M. Rafi. 2018. Enabling Resilience of Complex Engineered Systems Using Control Theory. *IEEE Transactions on Reliability*, Vol. 67, No. 1, pp. 53–65.

Study Impacts

This research pioneers a novel risk and resilience modeling and quantification framework that will lead to the realization of failure resilience for interdependent transportation systems. The proposed risk and resilience quantification and analysis research will provide a better understanding of system failures and the cascading effects of interdependent transportation systems for system designers and decision makers. Employing a novel Bayesian network approach will provide a new tool for system designers and decision makers to better design transportation systems and make optimal operational decisions against system disruptions induced by adverse failure events and further mitigate the risks of catastrophic failures. Further, incorporating risk and failure resilience into engineering design for resilient interdependent transportation systems will likely stimulate growth in several related infrastructure systems that are dependent on transportation systems, such as electrical power generation, healthcare, food supply chains, and more, which may suffer from possible catastrophic system failures and high maintenance costs.

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