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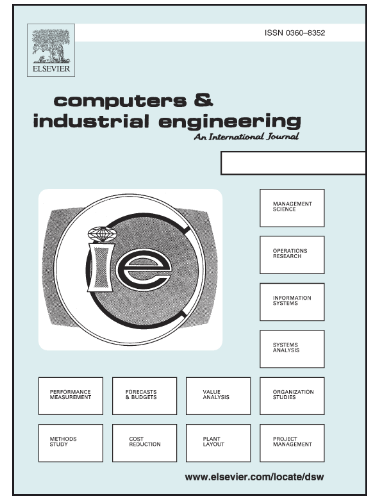

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Assessing Risk in Different Types of Supply Chains with a Dynamic Fault Tree

Abstract

Supply chain risk analysis is an important field in operations management and logistics. Identifying those risks, assessing the probability of those risks, and understanding how those risks change if mitigation strategies are implemented contribute to better supply chain risk management. Reliability analysis has a long tradition of assessing the probability of failure, and fault trees are typically used to understand how the failure of individual components can lead to system failure within an engineered system. More recently, fault trees have been proposed to assess the probability of a supply chain failure. Dynamic fault trees, which are relatively new in reliability analysis, model the dependency among possible component failure and how these probabilities change over time. This paper applies dynamic fault trees to model supply chain risk for different types of supply chains. The dynamic fault tree allows a firm to model complex interactions among suppliers and understand how those interactions impact its risk. The model incorporates an information system that relays information about the status of suppliers to the firm, and this information system could also fail. A Markov chain model and Monte Carlo simulation are used to numerically assess supply chain risk as modeled by these dynamic fault trees.

Keywords: risk analysis, supply chain risk, dynamic fault tree, Markov chain, Monte Carlo simulation

1. Introduction

Supply chains are vulnerable to disruptions due to globalization, the complexity of supply chains, and the frequency of disruptive events. Risks to a supply chain can stem from major disruptions, delays, forecast uncertainty, intellectual property, procurement actions, inventory, and capacity constraints (Chopra and Sodhi, 2004). Different events can threaten a supply chain, including internal sources (e.g., human errors, improper operations, communication problems) and external sources (e.g., natural disasters, terrorism, economic difficulties). For example, at the beginning of 2018, the fast-food chicken chain KFC apologized for running out of chicken in the United Kingdom (UK). Three weeks after the announcement, nearly 3 percent of KFC's restaurants in the UK remained closed. The source of problem was KFC's new approach for logistics. KFC switched from their prior logistics provider to DHL for warehousing and transportation and Quick Service Logistics for software for its information system. The collaboration among these three entities to manage a complex supply chain failed, and the new software system seemed to work incorrectly (Wilding, 2018). This example demonstrates the importance of being able to anticipate and manage supply chain risk and recover from breakdowns and disruptions. Supply chain risk management depends on having a comprehensive understanding and a thorough analysis of risks in a supply chain. Identifying and modelling risks can generate insight into the likelihood and severity of different risks in the supply chain and lead to proactive strategies that mitigate various sources of risks (Sodhi, 2014; Sheffi, 2005).

Supply chain risk management strategies usually include having multiple suppliers (Parlar and Perry, 1996; Currie, 1998), holding inventory, and responding quickly to problems (Christopher, 2000). Accurate inventory information can enhance supply chain performance (Fleisch and Tellkamp, 2005). An information system also plays a significant role in a supply chain. The information system is a real-time sharing and processing production information within a supply chain and can generate closer coordination between partners in a supply chain (Wu et al., 2006). In 2000, a plant in Philips Electronics experienced a fire. On of Philips' major customers, Nokia, quickly received information about Philips' difficulties via its computer. This ability allowed Nokia managers to respond quickly. A quality information system can increase supply chain flexibility (Gunasekaran and Ngai, 2004; Pereira, 2009; Williamson, Harrison, and Jordan, 2004) and enable a firm to more quickly mitigate risk by adjusting its inventory or coordinating different components (Yu, Yan, and Edwin Cheng, 2001; Lee, So, and Tang, 2000).

Several models have been proposed to help firms quantify the risk in their supply. More recently, fault trees have been used to estimate the probability of failure within a supply chain. Fault trees are used to model the reliability of engineered systems by showing the logical relationship between the input events and the output event. Sherwin et al. (Sherwin, Medal, and Lapp, 2016) develop a fault tree for a low volume, high value supply chain to model the likelihood of a delay in material flow and evaluate the benefits of different mitigation strategies. However, this type of static fault tree is unable to depict complex interactions between components in a supply chain in which those interactions may change over time. For example, the information system may relay that one supplier has encountered production difficulties to the firm's production manager. The production manager could use that information to manage the risk and avoid a disruption. This type of interaction between an information system, suppliers, and the production manager cannot be represented by a static fault tree.

A dynamic fault tree (DFT) has been recently introduced in reliability analysis in order to model components whose probabilities of failure change over time and when those probabilities are dependent on each other (Rao et al., 2009; Huang, Wang, and Liu, 2012). This paper extends the use of DFTs to assess supply chain risk, specifically for two types of supply chains. One supply chain is a main-backup supply chain in which a firm sources from a single supplier but can purchase from a backup supplier if the main supplier has production difficulties. The other type of supply chain is a mutual assistance supply chain in which a firm sources from two suppliers simultaneously. Both types of supply chains rely on an information system to relay information about the status of the supplier to the firm, but the information system can also fail.

This paper makes several unique contributions for supply chain risk analysis. First, the DFT represents a new model for two types supply chains risk analysis. Second, the Markov chain based on the DFT provides a mathematical model to calculate the expected time to failure of the supply chain as a function of the individual components' failure rates and repair rates. Finally, a Monte Carlo simulation is used to obtain a full probabilistic description of the time to failure and delivery time of the supply chain.

The rest of this study is organized as following ways: Section 2 reviews the literature in supply chain risk analysis and DFTs. Section 3 introduces the DFT for the two types of supply chains. Section 4 presents an illustrative example, including the analytical and the simulation methods for numerically calculating the failure rates and delivery times for the supply chains. Finally, conclusions are presented in Section 5.

2. Literature Review

The frequency of natural disasters and man-made accidents has increased during the past decades in industrialized countries (Coleman, 2006). Natural disasters, terrorism, and other unpredictable events increase the risk faced by globalized supply chains (Stewart, 1995; Brown et al., 2006; Chopra, Reinhardt, and Mohan, 2007). In addition, firms face less extreme risks such as suppliers who fail to deliver according to schedule or who have quality problems. Supply chain risk has been extensively studied in the literature, both from a qualitative and quantitative point of view. Qualitative studies often assess the likelihood of a risky event according to different levels, such as a rare event and likely event (Raj Sinha, Whitman, and Malzahn, 2004) and the severity of risk is often categorized from low severity to high severity (Norrman and Jansson, 2004). Qualitative studies usually recommend strategies for mitigating supply chain risk, such as postponement, speculation, hedging, and avoidance (Giannakis and Louis, 2011; Manuj and Mentzer, 2008; Giunipero and Aly Eltantawy, 2004; Christopher and Lee, 2004). Quantitative risk analysis estimates the probability of risky events based on past data (Tuncel and Alpan, 2010; Kleindorfer and Saad, 2005) and use mathematical models to determine the optimal strategies to manage and mitigate risks (Tomlin, 2006; Klibi, Martel, and Guitouni, 2010). Models for supply chain risk management may assess the value of holding additional inventory, purchasing from multiple suppliers, locating additional facilities, and moving production to another facility (Cui, Ouyang, and Shen, 2010; Schmitt and Singh, 2009; MacKenzie, Barker, and Santos, 2014; MacKenzie, Santos, and Barker, 2012).

Tools used in reliability engineering may be applicable to supply chain risk management. Failure Mode Effect Analysis and data mining have been suggested to identify and forecast risks in a supply chain (Zsidisin and Ritchie, 2008). Aqlan and Lam (Aqlan and Lam, 2015) propose that fault trees could be used to assess supply chain risk, and Sherwin et al. (Sherwin, Medal, and Lapp, 2016) design a fault tree to analyze the risk of delay in a low volume, high value supply chain. Low volume, high value supply chains such as airline manufacturing and nuclear power plant construction often have unique requirements that differ from mass-production supply chains. Using fault trees to model the risk in a low volume, high value supply chain is particularly appropriate because the fault tree can be used to assess the probability that the high-value product is delayed. The model developed by Sherwin et al. (Sherwin, Medal, and Lapp, 2016) is the only application that we know of in the literature that explicitly uses fault trees to model supply chain risk.

Fault trees in reliability are usually static and assume constant and independent probabilities and do not account for the sequence of failure events. In reality, the probability of a supplier failure may change over time, and one supplier's delay can influence the likelihood that another supplier is delayed. Sherwin et al. (Sherwin, Medal, and Lapp, 2016) do not consider the dependency and interplay between basic events which may impact supply chain risk. In the modern supply chain, information sharing among firms and other interactions occur that can mitigate risk, and a lack of information sharing can increase the risk. A DFT can better model these interactions over time than a traditional static fault tree. DFTs have been used in reliability analysis for complex engineering systems or computer systems, such as an aircraft power supply system (Huang, Wang, and Liu, 2012), a fault-tolerant flight control system (Yiping and Minghua, 1999), and a floating offshore wind turbine (Zhang et al., 2016). DFTs have not been used to model supply chain risk, and this paper presents a novel contribution by being the first to explore the use of DFTs for supply chain risk and disruptions.

There are many other commonly used methods for assessing the probability of failure when a system is complex and changes over time, such as dynamic Bayesian networks (DBNs) and artificial neural networks (ANNs). However, the DFT method has some unique advantages over other methods. ANNs are good to model non-linear and self-organizing systems. ANNs typically require a good set of data whereas a DFT might not require such an extensive set of data, and a DFT can be supplemented by eliciting information from experts. ANNs also contain hidden layers, which can be difficult to interpret and explain. Similar to a DFT, the DBN can model dependency and failure sequences. In a DBN, each node represents a certain meaning and is easily interpreted. Both DBNs and DFTs require knowledge of components in the system and of the relationships and dependencies among components. The major difference between a DFT and a DBN is that a DFT primarily relies on Boolean logic to model the failure relationships among components while a DBN uses conditional probabilities. It may be easier to understand and model the relationships among components using Boolean logic (e.g., the supply chain fails if two of three suppliers fail) than estimating conditional probabilities for all of the components. Overall, DFTs may be easier and more intuitive and require less data than ANNs and DBNs in modelling the dynamic mechanisms of a system (Zheng and Liu, 2009; Khakzad, Khan, and Amyotte, 2011; Angelopoulos and Cussens, 2008).

Analytical and simulation methods can be used to solve DFTs and calculate the probability of failure. Boudali et al. (Boudali, Crouzen, and Stoelinga, 2007) present the use of continuous-time Markov Chains to solve DFTs. Because the number of states and transition probabilities increase exponentially with the number of basic events, an efficient approximate Markov model has been suggested for DFTs (Yevkin, 2015). Other analytical methods for DFTs focus on generating the minimal cut set or using a binary decision diagram (Tang and Dugan, 2004; Cui et al., 2013) or translating a DFT to a Bayesian probabilistic network (Boudali and Duga, 2005; Montani et al., 2006). Since some DFTs are too complex for these analytical methods, Monte Carlo simulation has also been used to solve DFTs (Rao et al., 2009; Dai, Wang, and Jiao, 2011; Zhang and Chan, 2012). Simulations can enable more complex actions such as testing and maintenance for components, allow for dependent events, and use non-exponential probability distributions. MatCarloRe (Manno et al., 2012) integrates a fault tree into a Monte Carlo Simulink tool, but this tool only handles exponential, Weibull, and uniform distributions.

This article adopts the use of DFT from reliability analysis by modelling supply chain risk with a DFT. The logic relationship among suppliers, inventory, and information systems is represented by dynamic gates within the fault tree. We use Markov chains to analyze the DFT of supply chains. The failure rate of each supply chain is calculated using the Markov chain. Monte Carlo simulation is then used to calculate the probability the supply chain is late and to determine a probabilistic distribution over the actual delivery time of the supply chain.

3. Model

A supply chain's complexity can refer to the interconnectedness and interdependencies among components in a supply chain. A change in one element or component can induce changes in other components within the supply chain (Christopher, 2012). Different factors, such as parallel interactions, diversity of products, and the number of connections between nodes in the network, can increase complexity in a supply chain (Wilding, 1998; Vachon and Klassen, 2002; Choi, Dooley, and Rungtusanatham, 2001; Bozarth et al., 2009). This paper considers that the supply chain consists of suppliers, an information system, and inventory. The complexity of this supply chain mainly derives from the interaction and connectedness among these components. The interaction between different components in the supply chain changes over time. DFTs are useful to model dynamic factors, such as interactions in the supply chain. Different dynamic gates can be used to model different types of interactions. The model assumes that the different components and the interactions among these components can be identified. In reality, especially with very complicated supply chains, identifying all of the interactions can be challenging and quantifying or modelling these interactions may be even more difficult. If new suppliers or other components are added to supply chain, unknown relationships and interactions may be introduced to the supply chain. For example, the effect of one component's failure on other components may not be known, and failures that are assumed to be independent may actually be dependent.

Based on many real supply chain cases, the main three relationships between multiple suppliers are competitive supplier-supplier relationship, cooperative supplier-supplier relationship and co-opetitive supplier-supplier relationship (Choi et al., 2002; Choi and Krause, 2006). This paper constructs different DFTs for two typical supply chains by using five dynamic gates. The first type of supply chain represents a competitive relationship. If suppliers have a competitive relationship, they may not have direct communication and share information, and the firm chooses multiple suppliers. In this paper, a competitive relationship exists in a main-backup supply chain in which a firm sources from a single supplier but can source from a secondary supplier if the first supplier has problems. The second type of supply chain represents a cooperative relationship. If the cooperative relationship exists between suppliers, the suppliers will work together and have a close relationship. They will communicate with each other and share information. In this paper, a cooperative relationship exists in a mutual-assistance supply chain in which a firm sources from two suppliers. Although both suppliers have requirements to deliver the same product to the firm, if one supplier has problems, the other supplier may be able to increase its production rate. The DFTs for both types of supply chains can represent a high-volume supply chain, such as the food, clothing, or automobile industry, or a low-volume supply chain which produces one unit at a time, such as an airplane supply chain.

3.1. Main-Backup Supply Chain

A main-backup supply chain consists of a firm and a single or main supplier. The model assumes an information system informs the firm about the status of the main supplier's progress toward completing its order for the firm. If the firm receives information that the supplier has production difficulties, the firm will contact a backup supplier who can potentially fulfill the order. The backup supplier may also experience a failure or delay, however. The firm may also have inventory to mitigate the effects of any supply disruption. Finally, the model also captures the possibility that the the information system might fail in which case the firm would not be informed as quickly about the main supplier's production difficulties (Chopra and Sodhi, 2004).

A static fault tree consists of AND and OR gates. A DFT uses AND and OR gates but also introduces dynamic gates for modelling the reliability of a complex system over time. As depicted in Figure 1, the dynamic gates are: (i) the priority AND (PAND) gate, (ii) the sequence enforcing (SEQ) gate, (iii) the functional dependency (FDEP) gate, (iv) the spare (SPARE) gate and (v) the load sharing (LS) gate.

Each of these gates and their uses will be described in conjunction with the model to assess the risk of a main-backup supply chain and the risk of a mutual-assistance supply chain.

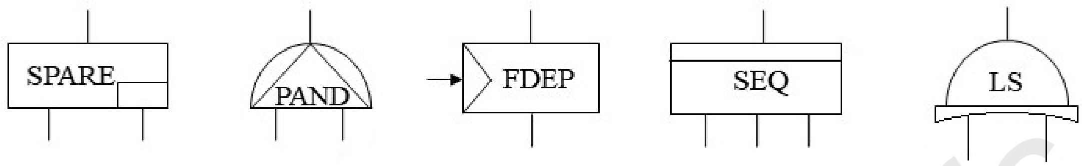


Figure 1: Dynamic Gates

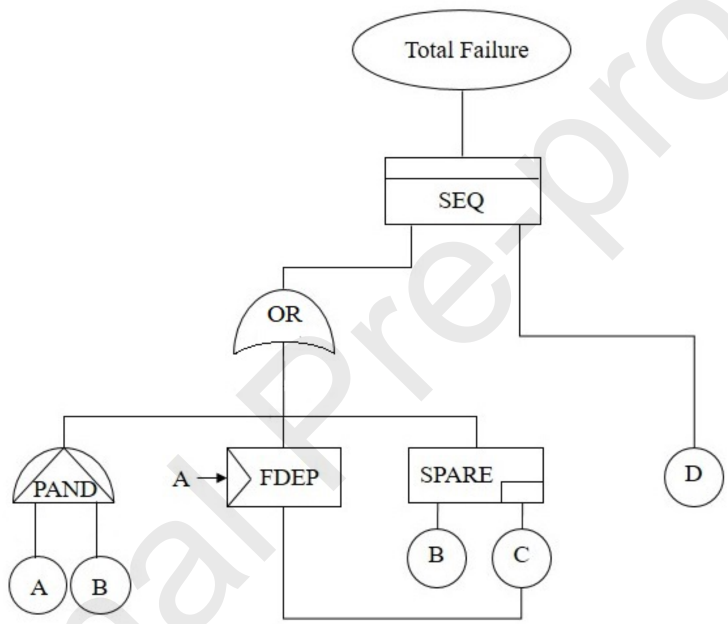


Figure 2: Dynamic Fault Tree for Main-Backup Supply Chain

This model has one main supplier, one backup supplier, an information system, and inventory in the supply chain. Figure 2 depicts the DFT for this supply chain. The PAND gate captures the failure of the output event when all basic events have failed in a pre-assigned order (from left to right in graphical notation). In the supply chain model, if the information system fails (event A) before the main supplier fails (event B), the information system will not alert the firm of the main supplier's difficulty. However, if the main supplier fails while the information is functioning correctly, the information system will alert the firm, who can source from the backup supplier. The PAND gate captures this relationship because the PAND gate only induces failure if A fails before B, but the system functions if B fails before A.

The FDEP gate depicts the events that are dependent upon a trigger event. In the supply chain model, if the information system fails (event A) before the main supplier fails (event B), then the failure information of the main supplier is not relayed to the firm or the backup supplier. In that case, the backup supplier will fail to be activated. The backup supplier's failure to activate (event C) would then be triggered by the occurrence of A, whose relationship is represented by the FDEP gate. The SPARE gate fails only when the number of surviving components is less than the minimum required (Manno et al., 2012). The SPARE gate models one or more principal components that can be replaced by one or more redundant components. In this supply chain, the main supplier and backup supplier can be considered as redundant components. If both the main supplier and the backup supplier fail to produce, the firm will not receive its supplies. The backup supplier can also fail even if the information system works correctly. An OR gate connects the PAND gate, the FDEP gate, and the SPARE gate. The OR gate connects the two failure modes in the main-backup supply chain. First, if the information system fails before the main supplier fails, the supply chain fails if the main supplier fails. The other failure scenario occurs if both the main supplier and backup supplier fail.

This OR gate is connected to the failure of inventory (event D) via the SEQ gate. A firm may have inventory or think it may have inventory which could be used if the firm fails to receive supply. The inventory may have quality problems, or the inventory could have been recently used without any record being made that the inventory has been used. The SEQ gate represents that the OR gate and inventory need to fail in a particular order. Failure in the supply chain occurs if the supply does not arrive and then inventory is not available.

3.2. Mutual-Assistance Supply Chain

Companies may have multiple suppliers to manufacture the same product simultaneously (Sculli and Wu, 1981; Chung, Talluri, and Narasimhan, 2010). If one supplier fails, the other supplier may be able to increase its production quantity or production rate. In a closely integrated supply chain, an information system could relay information about the status of each supplier to the firm and perhaps between the suppliers. We name this relationship a mutual-assistance supply chain. The unique relationship of these two suppliers is mutual help and simultaneous work. The mutual-assistance supply chain could also apply to two facilities owned by a single firm, and each facility produces the same product. Since a single firm directs both facilities, if one facility encounters production difficulties, the other facility could quickly be alerted and increase its production. We assume that inventory is not available in the mutual-assistance supply chain although the DFT could be extended to include inventory, similar to the main-backup supply chain.

The DFT for the mutual assistance supply chain is constructed according to different manufacturing scenarios and the structure of supply chain. If both suppliers manufacture a single unit for a low volume supply chain, the two suppliers work independently to manufacture the same product, but each supplier might have a different due date. If both suppliers manufacture products for a high volume supply chain, the two suppliers might both be delivering several units of the same product at the same time.

The SPARE gate is used to model the relationship between the main supplier and the backup supplier in the main-backup supply chain. In the previous model, the backup supplier will only start to meet the firm's order if the main supplier fails, but in the mutual-assistance supply chain, the two suppliers work simultaneously. We use a LS gate, as shown in Figure 1, to represent the relationship between these two suppliers. The LS gate fails only when both basic events fail, but these basic events may be probabilistically dependent. When one of basic event occurs (i.e., one of the suppliers fails), the likelihood that the other supplier will fail may increase because the latter is increasing its production quantity or production rate.

The model of the mutual-assistance supply chain considers two suppliers and an information system. In Figure 3, the DFT has one PAND gate with three basic events: the failure of the information system (event A), the failure of one supplier (event B), and the failure of the other supplier (event C). Similar to the main-backup supplier model, if the information system fails before either supplier fails, then the firm will not be notified about a supplier's production difficulties. Consequently, the other supplier will not be instructed to increase its production quantity or rate. The PAND gate provides the relationship between the information system failure and the production disruption of one of the two suppliers. Since both suppliers are working simultaneously, the two suppliers are connected via an OR gate. If the information system has failed, the failure of only one supplier is necessary to include supply chain failure. The FDEP gate is triggered by the information system's failure, and the dependent events are the production of the suppliers. Each supplier acts as a backup supplier to the other one, which is captured in the LS gate. An OR gate is used to connect the PAND gate, the FDEP gate, and the LS gate. The total failure of the supply chain (the OR gate) occurs if both suppliers fail or if one of the two suppliers fails given the information system fails first.

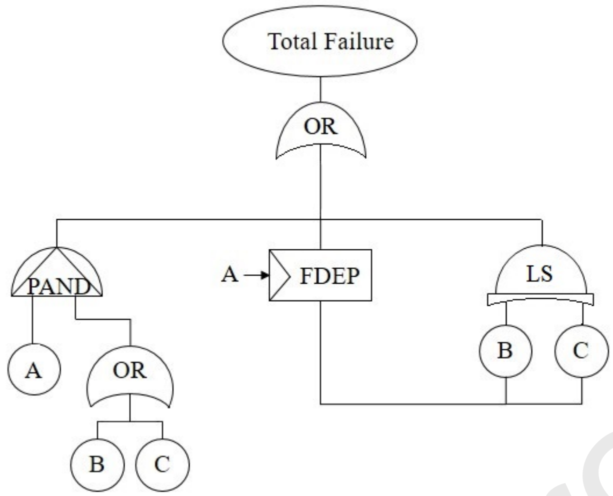


Figure 3: Dynamic Fault Tree for Mutual-Assistance Supply Chain

4. Illustrative Example

As is typical with DFTs, we translate each of the DFTs described previously to a Markov chain model. The Markov chain can be analytically solved to calculate the expected time to failure (Verma, Srividya, and Karanki, 2010). The Markov model is used to assess the impact of the components' failure rates and repair rates on the expected time to failure. Firms care about more than just the expected time to failure in the supply chain, however, and they also want to know when their product will be delivered. This illustrative example extends the Markov chain model to simulate the delivery time of the supply chain. Sensitivity analysis is performed on the parameters in order to demonstrate where the firm may want to focus its attention in order to mitigate its risk.

4.1. Main-Backup Supply Chain

A continuous-time Markov chain demonstrates the transition between different states of the supply chain based on the DFT. Since inventory is assumed to only be used if neither supplier can deliver on its order and does not impact the suppliers' failure, inventory is excluded from the Markov chain. The expected time to failure of a supply chain can be calculated from the corresponding Markov chain if the time to failure and time to repair follow exponential distributions.

Figure 4 shows the Markov chain for the main-backup supply chain as derived from the DFT in Figure 2. Each state in the Markov chain is defined by the three components (A is the information system, B is the main supplier, and C is the backup supplier) and whether each component is in an operating or failed state. In the figure, an arrow pointing down indicates the component is in a failed state. State 1 is the initial state of the main-backup supply chain in which all components operate. The times to failure and times to repair for each of the three components follow an exponential distribution. The failure rate is given by λ_X where X is the component A, B, or C, and the rate of repair is given by μ_X. The failure rate of the backup supplier C depends on whether or not the main supplier is operating. We assume the failure rate of the backup supplier increases if the main supplier has failed because the backup supplier has additional work to compensate for the failure of main supplier. If the main supplier is in a failed state, the failure rate of the backup supplier is λ_C. If the main supplier is in an operating state, the failure rate of the backup supplier is $\alpha\lambda_C$ where $0 < \alpha < 1$. Thus, state 1 transitions to state 4 with failure rate $\alpha\lambda_C$ because the main supplier B is operating, but state 3 transitions to system failure with failure rate λ_C because the main supplier has failed.

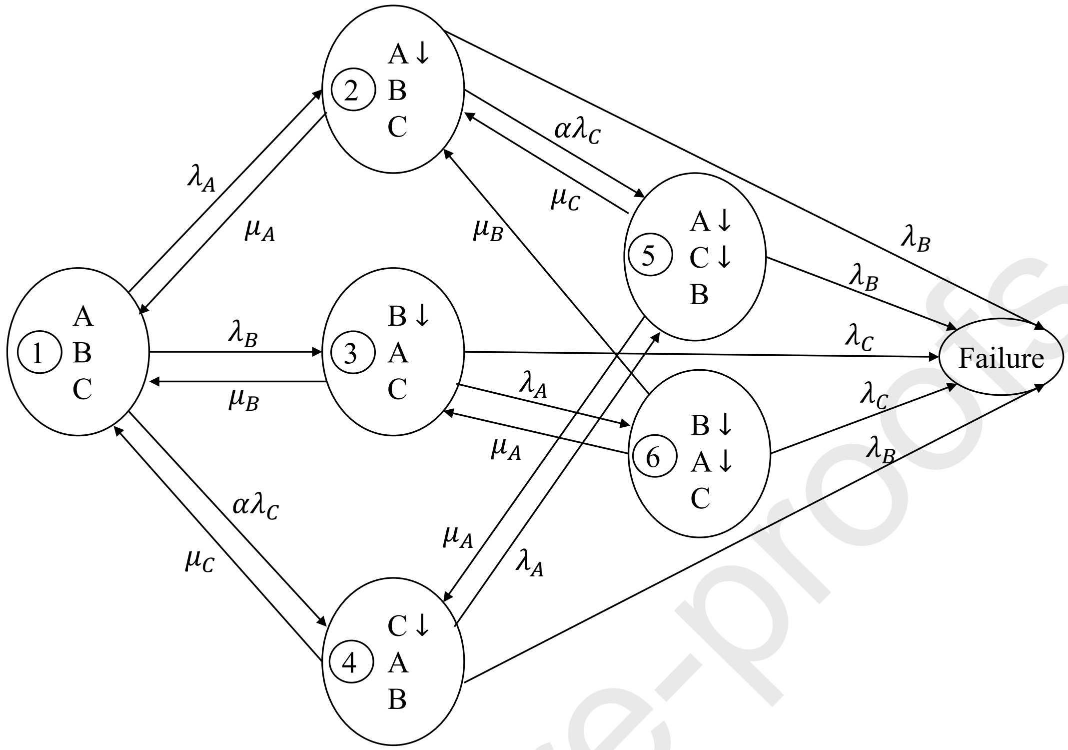


Figure 4: Markov Chain of the Main-Backup Supply Chain

As described in the DFT, the failure state in the Markov chain occurs if (i) the main supplier fails when the information system has already failed, or (ii) the main supplier and backup supplier both fail. The first type of failure occurs in Figure 4 when the system is in state 2 (the information system has failed) and then the main supplier fails. The second type of failure occurs in the figure when the system is in state 3 (the main supplier has failed) or state 6 (the information system and main supplier have failed) and the backup supplier fails. The second type of failure also occurs when the system is in state 4 (the backup supplier has failed) and the main supplier fails. If the system is in state 5 (the information system and backup supplier have failed) and then the main supplier fails, failure occurs for both reasons (i) and (ii). In this manner, the Markov chain replicates the failure modes depicted in the DFT.

Translating the DFT to the Markov chain and assuming exponentially distributed failure and repair times enables us to mathematically describe the expected time to failure for the main-backup supply chain. The expected time to failure given that the system is in state i is denoted by $E[T_F|\text{at state } i]$, and the expected time to state i given that the next transition is from state j to state i is denoted by $E[T_i|j\text{-}i]$. If the information system fails first, the system will transition from state 1 to state 2 with probability $\frac{\lambda_A}{\lambda_A+\lambda_B+\alpha\lambda_C}$. The expected time to transition from state 1 to state 2 is $E[T_2|1\text{-}2]$. Given the system is in state 2, the expected time to failure is $E[T_F|\text{at state } 2]$. Similarly, the probability the main supplier fails first equals $\frac{\lambda_B}{\lambda_A+\lambda_B+\alpha\lambda_C}$, and the probability the backup supplier fails first equals $\frac{\alpha\lambda_C}{\lambda_A+\lambda_B+\alpha\lambda_C}$. Given the system transitions from state 1 to state i, the expected time to failure equals the expected time to transition from state 1 to state i, $E[T_i|1\text{-}i]$, plus the expected time to failure given the system is in state i, $E[T_F|\text{at state } i]$. Given that all components are initially operating, the expected time from state 1 to the failure state, $E[T_F|\text{at state 1}]$, is as follows:

$$\begin{aligned} E[T_F|\text{at state 1}] = &\frac{\lambda_A}{\lambda_A+\lambda_B+\alpha\lambda_C}(E[T_F|\text{at state 2}]+E[T_2|\text{1-2}]) \\ &+\frac{\lambda_B}{\lambda_A+\lambda_B+\alpha\lambda_C}(E[T_F|\text{at state 3}]+E[T_3|\text{1-3}]) \\ &+\frac{\alpha\lambda_C}{\lambda_A+\lambda_B+\alpha\lambda_C}(E[T_F|\text{at state 4}]+E[T_4|\text{1-4}]) \end{aligned} \tag{1}$$

where

$$E[T_2|\text{1-2}]) = E[T_3|\text{1-3}] = E[T_4|\text{1-4}]) = \frac{1}{\lambda_A+\lambda_B+\alpha\lambda_C}$$

Given that the system transitions from state 1 to another state, the expected time of that transition equals the expected time that the system exits state 1. This expected transition time is the reciprocal of the sum of the failure rates.

Appendix A provides the expected times to failure given the system is in each one of the additional states (states 2 through 6). Combining these five equations with equation 1 enables us to calculate $E[T_F|\text{at state 1}]$. The complicated closed-formula for calculating $E[T_F|\text{at state 1}]$ provides little insight into the expected failure time, but a simple numerical example can demonstrate the impact of these parameters on the expected time to failure of the supply chain.

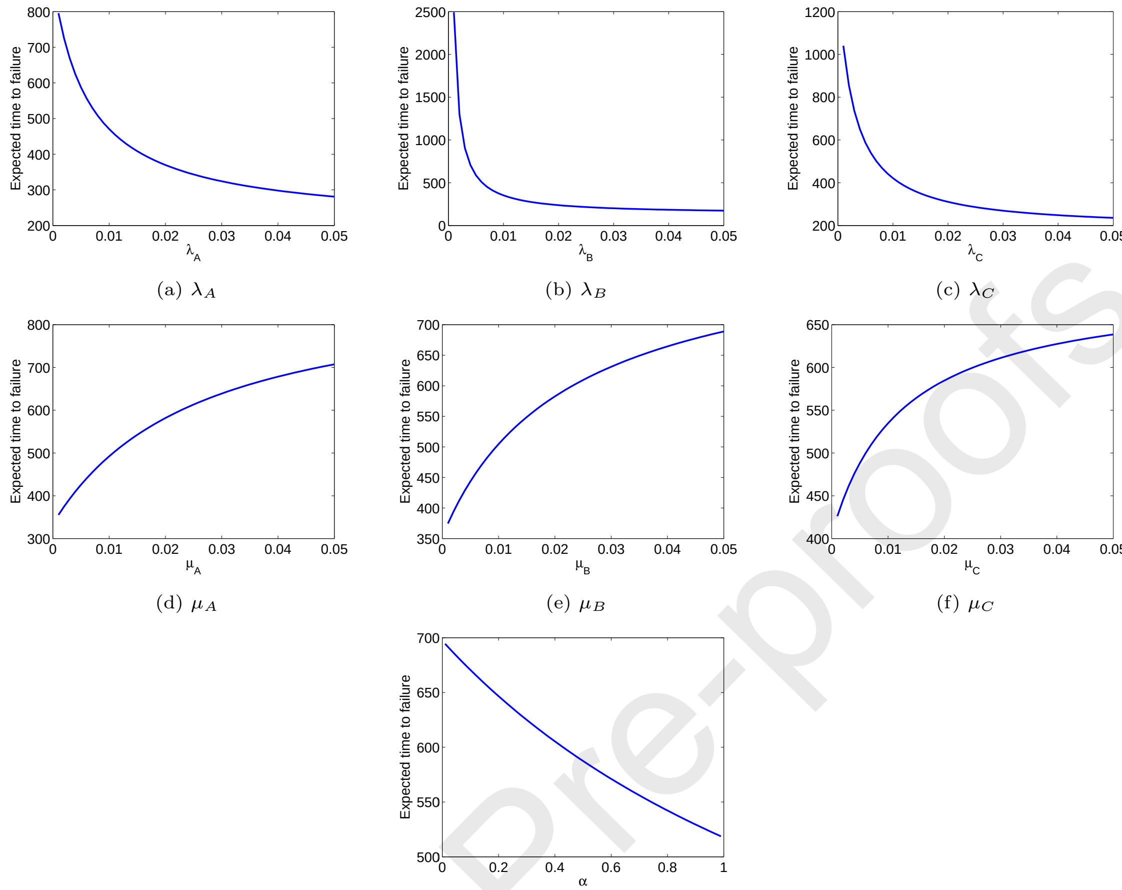
We assume that the mean time to failure of each component is 200 hours, and the mean time to repair each component is 48 hours. Then $\lambda_A = \lambda_B = \lambda_C = \frac{1}{200}$, $\mu_A = \mu_B = \mu_C = \frac{1}{48}$. We assume $\alpha = 0.5$. With these parameters, the expected time to failure equals 587 hours. Figure 5 depicts the sensitivity of the expected time to failure for each parameter. Not surprisingly, the expected time to failure increases as the failure rate of each component decreases and as the repair rate of each component increases. As α decreases, the failure rate of the backup supplier C decreases, and the supply chain's expected time to failure increases.

The expected time to failure is convex with respect to λ_A, λ_B, λ_C, and α. This means that the marginal decrease in the expected time to failure is greater when the failure rates are small than when failure rates are large. The expected time to failure is concave with respect to μ_A, μ_B, and μ_C, which signifies that the marginal increase in the expected time to failure is greater when the repair rates are small than when the repair rates are large. This effect is most noticeable with respect to the failure rates. The expected time to failure of a system where failure follows an exponential distribution equals the reciprocal of the system's failure rate. The expected time to failure of the supply chain exhibits a similar shape in relation to the failure rate of each component.

The supply chain's expected time to failure is most sensitive to the main supplier's failure rate λ_B. This is reasonable because the failure of the supply chain only occurs if the main supplier has failed. The expected time to failure is more sensitive to the backup supplier's failure rate λ_C than the information system's failure rate λ_A. This is due in large part to the PAND gate in the DFT. For failure to occur due to the information system, the information system must fail before the main supplier fails. Since the supply chain continues to operate if the information system fails after the main supplier fails, the effect of the information system's failure rate on the expected time to failure is limited.

The supply chain's expected time to failure is equally sensitive to the repair rate for both the information system μ_A and the main supplier μ_B. The expected time to failure is less sensitive to the backup supplier's repair rate μ_C. The backup supplier's repair rate has the smallest impact on the expected time to failure because the backup supplier fails less frequently than either the information system or main supplier. The failure rate for the backup supplier $\alpha\lambda_C$ is less than λ_A or λ_B.

A Monte Carlo simulation of the Markov chain model based on the DFT generates a full probability distribution of the supply chain's failure time, depicted in Figure 6. The simulation also does not consider inventory in supply chain. The simulation time is conducted for 86,400 hours or 10 years, during which 118 supply chain failures occur. The distribution is heavily skewed right, and approximately half of the failures occur in less than 1000 hours. A small probability exists that the failure time will be greater than 2500 hours. This simulation demonstrates that although the expected time to failure is 587 hours, the



(a) λ_A (b) λ_B (c) λ_C

(d) μ_A (e) μ_B (f) μ_C

(g) α

Figure 5: Sensitivity of the Expected Time to Failure for Different Parameters in Main-Backup Supply Chain

expected time is heavily influenced by the right tail. The supply chain is very likely to fail well before the expected time to failure.

The simulation can also be used to calculate the delivery time for the product. Since inventory is not delivered, we ignore the role of inventory in this section. We only consider the failure and repair of suppliers and the failure of the information system. As discussed earlier, we measure the time to failure and time to repair for the two suppliers and the information system. The standard delivery time is the time it takes for the main supplier to deliver the product if the supplier does not fail. If a supplier fails and then recovers, we assume the supplier can increase its rate of production in order to make up for lost time. The parameter k, where $0 < k < 1$, is used to represent the extent to which the supplier can increase its rate of production after recovering from a failure. If a supplier fails or encounters production difficulties, the actual delivery time is calculated by equation (2).

$$\begin{aligned} \text{actual delivery time} &= \text{time to failure} + \text{time to repair} \\ &\quad + k * (\text{standard delivery time} - \text{time to failure}) \end{aligned} \tag{2}$$

The backup supplier only starts working on the product if the main supplier fails. The delivery time of the backup supplier includes the time when it is idle. The standard delivery time is set to 200 hours in the simulation, which equals the mean time to failure of the main supplier, and $k = 0.5$. If the actual delivery calculated with equation (2) is shorter than the standard delivery time, we assume the actual delivery time equals the standard delivery time. After simulating the supply chain for 10 years, Figure 7

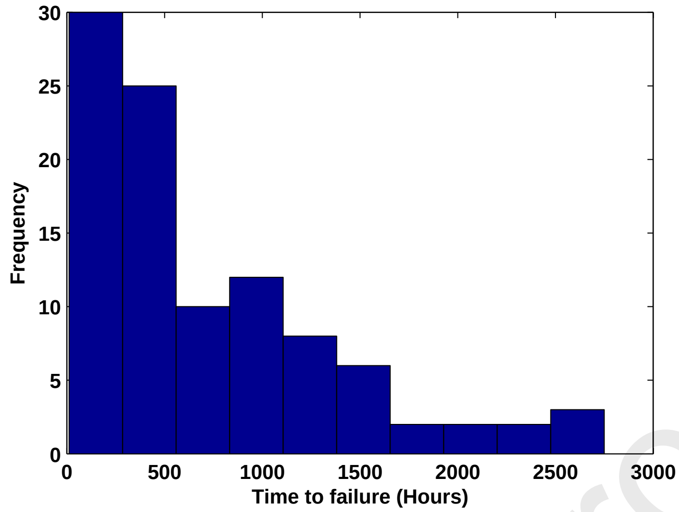


Figure 6: Histogram of Simulated Time to Failure of the Main-Backup Supply Chain

and Figure 8 depict the histograms of delivery time for the main and backup suppliers, respectively. If the backup supplier is not used, the delivery time to the firm is the delivery time for the main supplier. If the backup supplier is activated, the delivery time to the firm is the shorter delivery time for the main supplier and the backup supplier. The delivery time to the firm is depicted in Figure 9.

204 deliveries occur in the simulation. The mean delivery time to the firm is 209 hours, and the standard deviation is 20 hours. Deliveries arrive late 23.0% of the time. The backup supplier is not activated if the information system fails before the main supplier fails. The backup supplier is activated in 55.0% of the deliveries, but the delivery time of the backup supplier is shorter than the main supplier's delivery time in only 3.9% of the deliveries. Thus, although the backup supplier is frequently activated, it usually is a waste of money for the firm because the main supplier recovers more quickly. Controlling the failure of the main supplier is more important than engaging with the backup supplier.

4.2. Mutual-Assistance Supply Chain

A similar analysis is conducted for the mutual-assistance supply chain in which two suppliers are simultaneously manufacturing a product. The DFT in Figure 3 is translated to the Markov chain model depicted in Figure 10. Each state in the Markov chain is defined by the three components and whether each component is in an operating or failed state. In the figure, an arrow pointing down indicates the component is in a failed state. A is the information system, and B and C are the two suppliers which operate simultaneously. These components begin in an operational state, as depicted in state 1. As with the main-backup supply chain, the times to failure and times to repair for each of the three components follow an exponential distribution where λ_A, λ_B, and λ_C are the failure rates and μ_A, μ_B, and μ_C are the repair rates. If the information system does not fail, the failure rate of each supplier depends on whether or not the other supplier is operating. We assume the failure rate of one supplier increases if the other supplier has failed because that supplier has additional work to compensate for the failure of the other supplier. If one supplier is in a failed state, the failure rate of the other supplier is λ_X/β where X is the supplier B or C and $0 < \beta < 1$. Thus, state 1 transitions to state 3 with failure rate λ_B because the suppliers B and C are operating, but state 4 transitions to system failure with failure rate λ_B/β because supplier C has already failed. If the information system fails first, state 1 transitions to state 2 with failure rate λ_A. In this situation, once one supplier fails, the supply chain will fail. Thus, state 2 transitions to system failure with failure rate $\lambda_B + \lambda_C$.

As described in the DFT, the failure state in the Markov chain occurs if both suppliers fail given the information system operates, or if one of two suppliers fails given the information system fails first. The

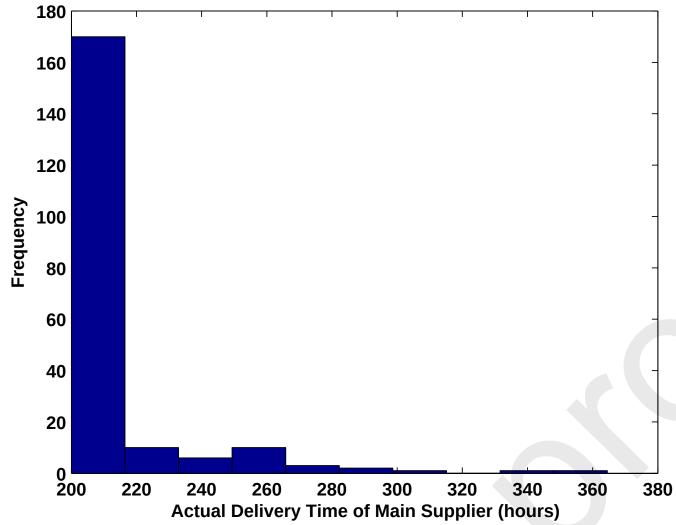


Figure 7: Simulated Actual Delivery Time of Main Supplier

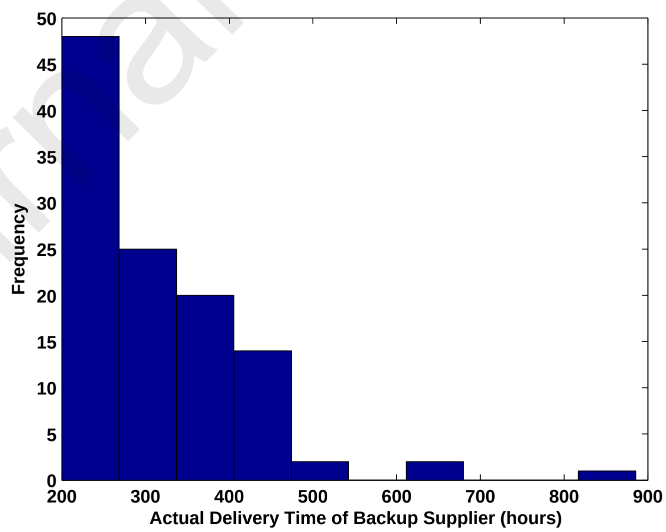


Figure 8: Simulated Actual Delivery Time of Backup Supplier

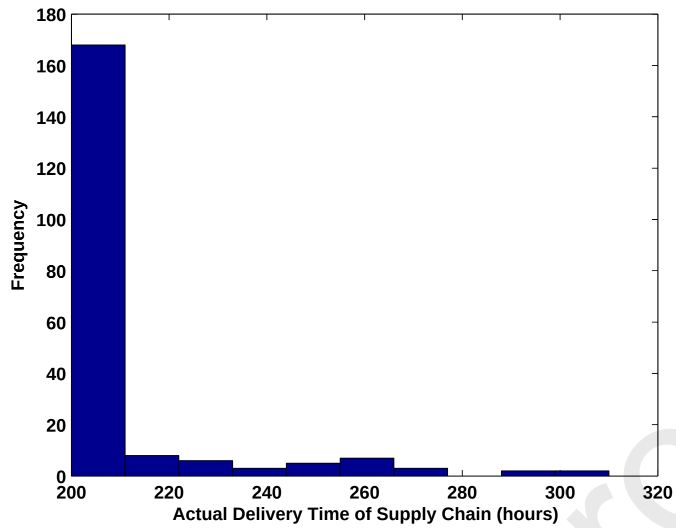


Figure 9: Simulated Actual Overall Delivery Time of Supply Chain

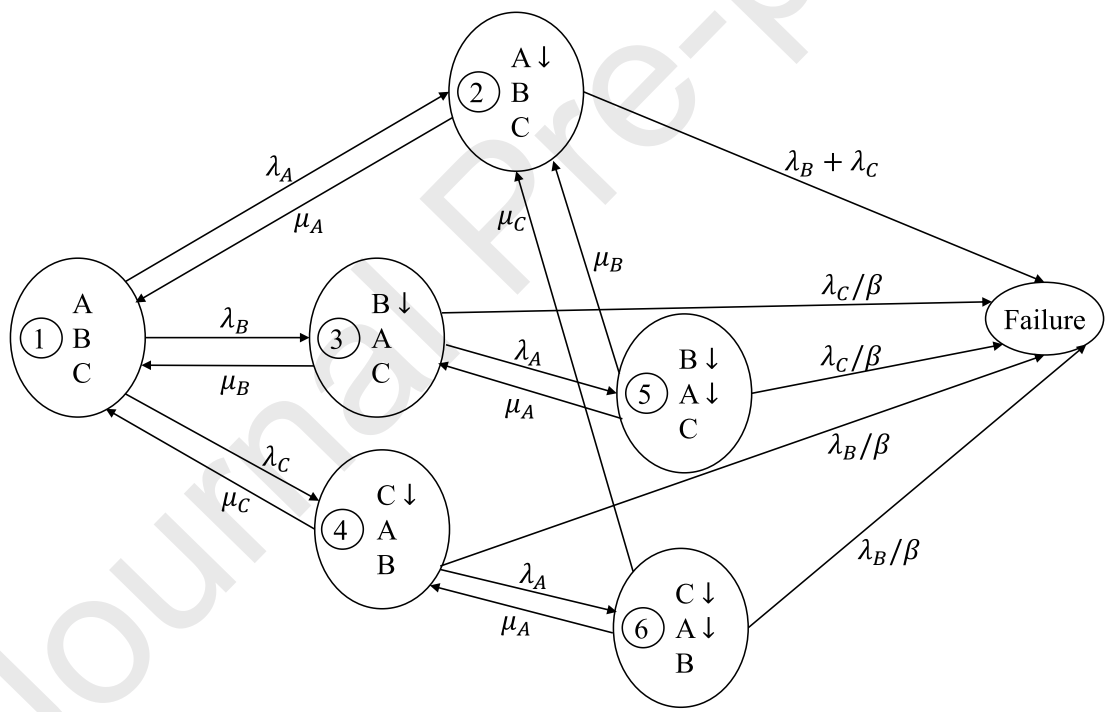


Figure 10: Markov Chain of the Mutual-Assistance Supply Chain

top arrow pointing into the failure in Figure 10 indicates that one of two suppliers has failed. Other arrows pointing into the failure in Figure 10 indicates that the second supplier has failed. Similar to the main-backup supply chain, we can use the Markov chain to calculate the expected time to failure. This requires writing the equation for the expected time to failure given that the supply chain is in state i for each of 6 states in the supply chain. Given that all components are initially operating, the expected time from state 1 to the failure state, $E[T_F|\text{at state 1}]$, is as follows:

$$\begin{aligned} E[T_F|\text{at state 1}] = & \frac{\lambda_A}{\lambda_A+\lambda_B+\lambda_C}(E[T_F|\text{at state 2}]+E[T_2|\text{1-2}]) \\ & +\frac{\lambda_B}{\lambda_A+\lambda_B+\lambda_C}(E[T_F|\text{at state 3}]+E[T_3|\text{1-3}]) \\ & +\frac{\lambda_C}{\lambda_A+\lambda_B+\lambda_C}(E[T_F|\text{at state 4}]+E[T_4|\text{1-4}]) \end{aligned} \tag{3}$$

where

$$E[T_2|\text{1-2}]) = E[T_3|\text{1-3}] = E[T_4|\text{1-4}]) = \frac{1}{\lambda_A+\lambda_B+\lambda_C}$$

Given that the system transitions from state 1 to another state, the expected time of that transition equals the expected time the system exits state 1. This expected transition time is the reciprocal of the sum of the failure rates. Appendix B provides the expected times to failure given the system is in each one of the additional states (states 2 through 6). Combining these five equations with equation 3, we can calculate $E[T_F|\text{at state 1}]$.

A numerical example demonstrates the impact of these parameters on the expected time to failure of the supply chain. The mean time to failure of each component is 200 hours, and the mean time to repair for each component is 48 hours. Then $\lambda_A = \lambda_B = \lambda_C = \frac{1}{200}$ and $\mu_A = \mu_B = \mu_C = \frac{1}{48}$. We assume $\beta = 0.5$. With these parameters, the expected time to failure equals 437 hours.

Figure 11 depicts the sensitivity of the expected time to failure for each parameter. The expected time to failure increases as the failure rates of two suppliers decrease and as the repair rates of two suppliers increase. The expected time to failure is equally sensitive to the failure rates of two suppliers, λ_B and λ_C, and equally sensitive to the repair rates of the two suppliers, μ_B and μ_C. Since the two suppliers are identical entities within the supply chain and work simultaneously, their failure and repair rates have identical impacts on supply chain's expected time to failure. The expected time to failure increases very rapidly if the supplier's failure rate is less than 0.005. The expected time to failure is less sensitive to the information system's failure rate λ_A and repair rate μ_A. The information system's failure rate has less impact than the suppliers' failure rates because the supply chain does not fail if the information system fails after one of the suppliers fails. As β increases, the failure rate of one supplier if the other supplier has already failed decreases. Consequently, the supply chain's expected time to failure increases in approximately a linear fashion.

A Monte Carlo simulation of the Markov chain model based on the DFT provides a full probability distribution of the supply chain's failure time. The histogram of the simulated failure time of the mutual-assistance supply chain is shown in Figure 12. The distribution is skewed right. The time to failure is heavily influenced by extreme values in the distribution. The supply chain is very likely to fail before the expected time failure.

Similar to the main-backup supply chain, we simulate the delivery time for the mutual-assistance supply chain, and equation (2) is used to calculate the actual delivery time if a supplier has production difficulties. The standard delivery time is set to 200 hours in the simulation, which equals the mean time to failure of each supplier, and $k = 0.5$. Since each supplier is identical, the simulated delivery time of one of the suppliers is shown in Figure 13. As with the main-backup supply chain, the overall delivery time to the firm is the minimum delivery time of the two suppliers, as depicted in Figure 14.

The mean of the actual delivery time is 202 hours, or about 8.5 days. The standard deviation is 9 hours. Although the parameters for the main-backup supply chain and the mutual-assistance supply chain are the same, the mutual-assistance supply chain needs less time to deliver products since both suppliers are working simultaneously in the mutual-assistance supply chain. Only 6% of trials in the mutual-assistance supply chain have late deliveries, compared with 23% in the main-backup supply chain. Although both types of supply chain have a supplier failing about 1/3 of the time, the firm usually receives its order by the due date in the mutual-assistance supply chain. In the main-backup supply chain, the delivery is late almost 75% of the time in which the main supplier encounters a failure. The main-backup supply chain has a larger probability of being late than in the mutual-assistance supply chain because

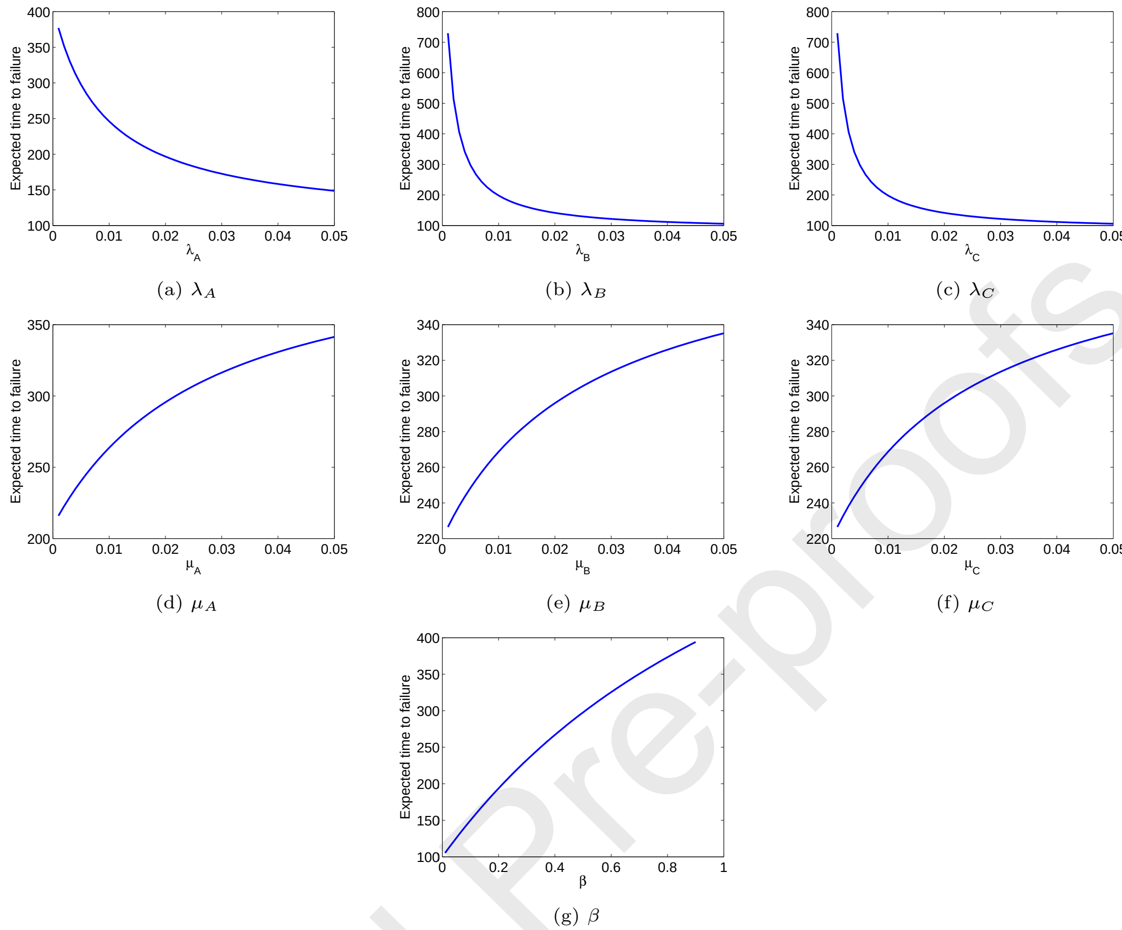


Figure 11: Sensitivity of the Expected Time to Failure for Different Parameters in Mutual-Assistance Supply Chain

the mutual-assistance supply chain has two suppliers working simultaneously.

5. Conclusions

This paper is the first to model and assess risk in a supply chain using DFTs. Two types of supply chains are analyzed: the main-backup supply chain in which a backup supplier can be engaged in case the main supplier has production difficulties and the mutual-assistance supply chain in which a firm sources from two suppliers simultaneously. The PAND gate, the FDEP gate, the SPARE gate, the LS gate, and the SEQ gate enable the DFT to model the complex interactions among components in order to assess the reliability of a system over time. Applying these concepts to a supply chain incorporates the use of an information system that relays information about the main supplier to the firm. The models are illustrated using Markov chains and Monte Carlo simulation for a low-volume supply chain. Some simple examples are presented to illustrate how a firm could use these models and simulations to quantify its risk and mitigate its risk.

In this paper, a low-volume supply chain is a supply chain that manufactures a single product during a period of time, such as an airplane or nuclear power plant components. It can take several months or even longer time to manufacture such a product. High-volume supply chains, such as a food, clothing, or automotive supply chain, produce thousands of products in a short time. High-volume supply chains are interested in delivering multiple units in time. The DFTs used in this paper can be extended to a high-volume supply chain by assuming that the failure of supply chain occurs when multiple units are

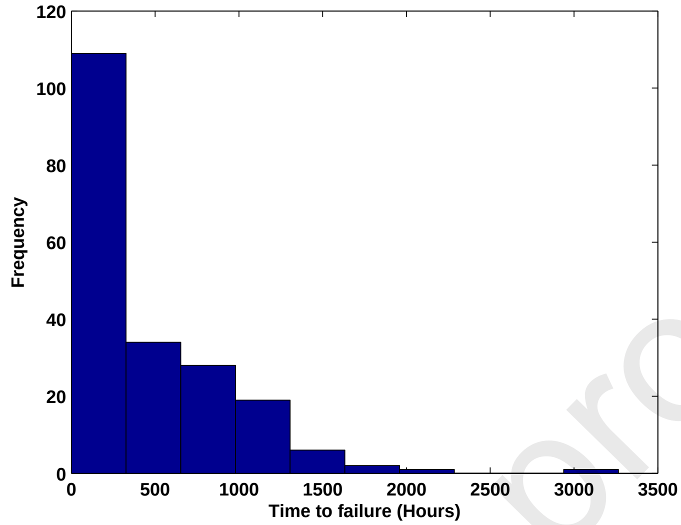


Figure 12: Histogram of Simulated Time to Failure of the Mutual-Assistance Supply Chain

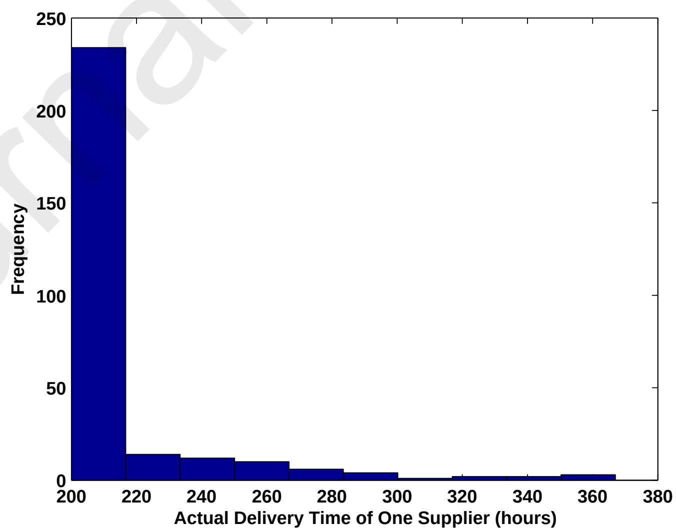


Figure 13: Histogram of Simulated Actual Delivery Time of One Supplier

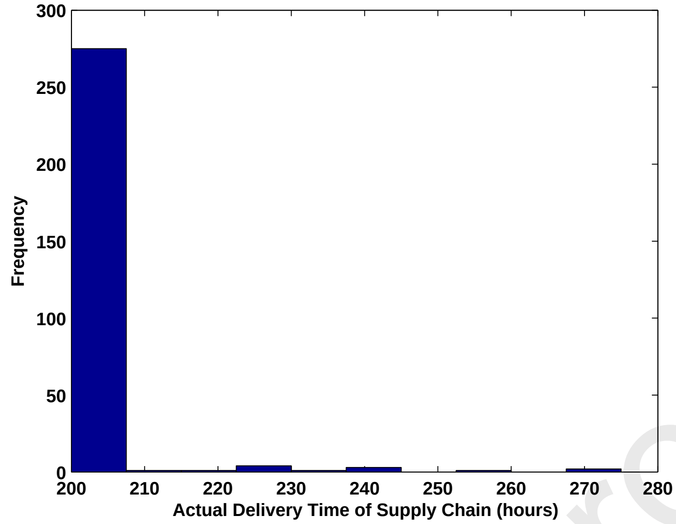


Figure 14: Histogram of Simulated Actual Overall Delivery Time of Supply Chain

not made or delivered. The Markov chain models and Monte Carlo simulations can also be used to solve DFTs modelling the risk of a high-volume supply chain.

Since this paper represents the first model of supply chain risk using DFTs, the supply chain models in this paper are relatively simple. These simple models are presented in order to demonstrate how the dynamic gates could be used within a fault tree to model supply chain risk and how this model could be applied to different types of supply chains. Future research can extend the DFTs to more realistic representations of supply chains with many more suppliers and multiple echelons. This will enable supply chain managers to assess the risk in those supply chains, understand how the risk changes over time, explore the dependencies among different entities in the supply chain, and help them determine the best risk management strategies. Second, the models in this paper assume exponential distributions, and future research could explore the implications of using other types of distributions including Weibull, uniform, and gamma distributions. Finally, in the case of a real supply chain, data could be used to fit distributions and understand the dependencies among suppliers.

Appendix A. The Expected Time from Different States to Failure State in the Main-Backup Supply Chain

$$\begin{aligned}
E[T_F|\text{at state 2}] &= \frac{\lambda_B}{\lambda_B+\alpha\lambda_C+\mu_A}(E[T_F|\text{2-F}]) \\
&+\frac{\alpha\lambda_C}{\lambda_B+\alpha\lambda_C+\mu_A}(E[T_F|\text{at state 5}]+E[T_5|\text{2-5}]) \\
&+\frac{\mu_A}{\lambda_B+\alpha\lambda_C+\mu_A}(E[T_F|\text{at state 1}]+E[T_1|\text{2-1}]) \\
E[T_F|\text{2-F}] = E[T_5|\text{2-5}] = E[T_1|\text{2-1}] &= \frac{1}{\lambda_B+\alpha\lambda_C+\mu_A}
\end{aligned} \tag{A.1}$$

$$\begin{aligned}
E[T_F|\text{at state 3}] &= \frac{\lambda_C}{\lambda_A+\lambda_C+\mu_B}(E[T_F|\text{3-F}]) \\
&+\frac{\mu_B}{\lambda_A+\lambda_C+\mu_B}(E[T_F|\text{at state 1}]+E[T_1|\text{3-1}]) \\
&+\frac{\lambda_A}{\lambda_A+\lambda_C+\mu_B}(E[T_F|\text{at state 6}]+E[T_6|\text{3-6}]) \\
E[T_F|\text{3-F}] = E[T_1|\text{3-1}] = E[T_6|\text{3-6}] &= \frac{1}{\lambda_A+\lambda_C+\mu_B}
\end{aligned} \tag{A.2}$$

$$\begin{aligned}
E[T_F|\text{at state 4}] &= \frac{\lambda_B}{\lambda_A+\lambda_B+\mu_C}(E[T_F|\text{4-F}]) \\
&+\frac{\lambda_A}{\lambda_A+\lambda_B+\mu_C}(E[T_F|\text{at state 5}]+E[T_5|\text{4-5}]) \\
&+\frac{\mu_C}{\lambda_A+\lambda_B+\mu_C}(E[T_F|\text{at state 1}]+E[T_1|\text{4-1}]) \\
E[T_F|\text{4-F}] = E[T_5|\text{4-5}] = E[T_1|\text{4-1}] &= \frac{1}{\lambda_A+\lambda_B+\mu_C}
\end{aligned} \tag{A.3}$$

$$\begin{aligned}
E[T_F|\text{at state 5}] &= \frac{\lambda_B}{\mu_A+\lambda_B+\mu_C}(E[T_F|\text{5-F}]) \\
&+\frac{\mu_A}{\mu_A+\lambda_B+\mu_C}(E[T_F|\text{at state 4}]+E[T_4|\text{5-4}]) \\
&+\frac{\mu_C}{\mu_A+\lambda_B+\mu_C}(E[T_F|\text{at state 2}]+E[T_2|\text{5-2}]) \\
E[T_F|\text{5-F}] = E[T_4|\text{5-4}] = E[T_2|\text{5-2}] &= \frac{1}{mu_A+\lambda_B+\mu_C}
\end{aligned} \tag{A.4}$$

$$
\begin{aligned}
E[T_F|\text{at state 6}] &= \frac{\lambda_C}{\mu_A+\mu_B+\lambda_C}(E[T_F|\text{6-F}]) \\
&+\frac{\mu_B}{\mu_A+\mu_B+\lambda_C}(E[T_F|\text{at state 2}]+E[T_2|\text{6-2}]) \\
&+\frac{\mu_A}{\mu_A+\mu_B+\lambda_C}(E[T_F|\text{at state 3}]+E[T_3|\text{6-3}]) \\
E[T_F|\text{6-F}] = E[T_2|\text{6-2}] = E[T_3|\text{6-3}] &= \frac{1}{\mu_A+\mu_B+\lambda_C}
\end{aligned} \tag{A.5}
$$

Appendix B. The Expected Time from Different States to Failure State in the Mutual-Assistance Supply Cahin

$$\begin{aligned} E[T_F|\text{at state 2}] &= \frac{\lambda_B+\lambda_C}{\lambda_B+\lambda_C+\mu_A}(E[T_F|\text{2-F}]) \\ &+\frac{\mu_A}{\lambda_B+\lambda_C+\mu_A}(E[T_F|\text{at state 1}]+E[T_1|\text{2-1}]) \\ E[T_F|\text{2-F}] &= E[T_1|\text{2-1}] = \frac{1}{\lambda_B+\lambda_C+\mu_A} \end{aligned} \tag{B.1}$$

$$\begin{aligned} E[T_F|\text{at state 3}] &= \frac{\lambda_C/\beta}{\lambda_A+\lambda_C/\beta+\mu_B}(E[T_F|\text{3-F}]) \\ &+\frac{\lambda_A}{\lambda_A+\lambda_C/\beta+\mu_B}(E[T_F|\text{at state 5}]+E[T_5|\text{3-5}]) \\ &+\frac{\mu_B}{\lambda_A+\lambda_C/\beta+\mu_B}(E[T_F|\text{at state 1}]+E[T_1|\text{3-1}]) \\ E[T_F|\text{3-F}] = E[T_5|\text{3-5}] &= E[T_1|\text{3-1}] = \frac{1}{\lambda_A+\lambda_C/\beta+\mu_B} \end{aligned} \tag{B.2}$$

$$\begin{aligned} E[T_F|\text{at state 4}] &= \frac{\lambda_B/\beta}{\lambda_A+\lambda_B/\beta+\mu_C}(E[T_F|\text{4-F}]) \\ &+\frac{\lambda_A}{\lambda_A+\lambda_B/\beta+\mu_C}(E[T_F|\text{at state 6}]+E[T_6|\text{4-6}]) \\ &+\frac{\mu_C}{\lambda_A+\lambda_B/\beta+\mu_C}(E[T_F|\text{at state 1}]+E[T_1|\text{4-1}]) \\ E[T_F|\text{4-F}] = E[T_6|\text{4-6}] &= E[T_1|\text{4-1}] = \frac{1}{\lambda_A+\lambda_B/\beta+\mu_C} \end{aligned} \tag{B.3}$$

$$\begin{aligned} E[T_F|\text{at state 5}] &= \frac{\lambda_C/\beta}{\mu_A+\lambda_C/\beta+\mu_B}(E[T_F|\text{5-F}]) \\ &+\frac{\mu_B}{\mu_A+\lambda_C/\beta+\mu_B}(E[T_F|\text{at state 2}]+E[T_2|\text{5-2}]) \\ &+\frac{\mu_A}{\mu_A+\lambda_C/\beta+\mu_B}(E[T_F|\text{at state 3}]+E[T_3|\text{5-3}]) \\ E[T_F|\text{5-F}] = E[T_2|\text{5-2}] &= E[T_3|\text{5-3}] = \frac{1}{\mu_A+\lambda_C/\beta+\mu_B} \end{aligned} \tag{B.4}$$

$$
\begin{aligned}
E[T_F|\text{at state 6}] &= \frac{\lambda_B/\beta}{\mu_A+\lambda_B/\beta+\mu_C}(E[T_F|\text{6-F}]) \\
&+\frac{\mu_C}{\mu_A+\lambda_B/\beta+\mu_C}(E[T_F|\text{at state 2}]+E[T_2|\text{6-2}]) \\
&+\frac{\mu_A}{\mu_A+\lambda_B/\beta+\mu_C}(E[T_F|\text{at state 4}]+E[T_4|\text{6-4}]) \\
E[T_F|\text{6-F}] = E[T_2|\text{6-2}] = E[T_4|\text{6-4}] &= \frac{1}{\mu_A+\lambda_B/\beta+\mu_C}
\end{aligned}
\tag{B.5}
$$

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Highlights:

- Dynamic fault tree allows a firm to model complex interactions among suppliers
- Markov chains and simulations can assess risk modeled by dynamic fault trees
- The e□ect of the information system's failure rate on total failure is limited
- Reducing failures of the main supplier is more important than the backup supplier
- Main-backup supply chain is more likely to be late than mutual-assistance one