Proactive Cost-Effective Risk Mitigation in a Low Volume High Value Supply Chain Using Fault-Tree Analysis

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Abstract

In this paper we use a well-accepted methodology, fault-tree analysis, to assess risk and proactively propose a cost-effective mitigation strategy within a low volume high value supply chain and base its formulation on the bill of materials of a manufactured product. The top-level event of interest represents the delay in delivering a product to a customer and lower-level events represent the causes and associated probabilities of disruptions within the supply chain for the product being studied. Supply chain risk mitigation strategies have been well documented in academic literature. However, much of what has been documented addresses such topics as facility location, inventory buffers, and is generally focused on response strategies once the risk has been realized. This paper presents a robust method to represent the system of suppliers within a supply chain as a fault-tree and proactively determine the optimum risk mitigation strategy for the portfolio. The approach is illustrated via real-world numerical scenarios based on hypothetical data sets and the results are presented. An optimum strategy to introduce a second improved source is selected that reduces the overall supply chain risk by 6.5% at a relatively modest cost of less than $10,000 in lieu of both more costly and less costly scenarios that do not provide the same level of risk reduction.

Keywords

Supply chain; fault-tree analysis; supplier selection; risk mitigation

1 Introduction

In this paper we address the problem of being able to determine areas of risk within a supply chain proactively and subsequently implement an effective mitigation strategy to address those risks. Specifically, a quantitative, prevention-based methodology using fault-tree analysis is employed. The unreliability of the supply chain is modeled as a fault-tree whereby the top event represents a critical assembly and basic events are based on the critical assembly's bill of materials. The many individual components and subassemblies comprising the critical assembly are represented by events within the fault-tree. Event and gate probabilities are a function of the unreliability of delivering the particular component, subassembly, or critical assembly on-time. As a result, the completed fault-tree provides insight into the at-risk areas within the supply chain being studied, an opportunity to apply interdiction strategies at various points within the supply chain, and study the consequences of implementing particular actions in advance of executing those strategies.

1.1 Motivation

Within recent years, a number of factors related to how businesses are managed have exposed supply chains to additional risks. These factors include: (1) a focus on efficiency rather than effectiveness, (2) supply chain globalization, (3) focused factories and centralized distribution, (4) a trend toward outsourcing, and (5) reduction of the supply base [1]. Industries that rely on low volume, high value, long lead time products have greater consequences when disruptions occur and especially if risks are realized at the latter stages of production or downstream within the supply chain. Examples of such industries include airline manufacturing [2], nuclear power plant construction [3], and shipbuilding [4]. Further compounding the risk exposure within these supply chains is that by nature, manufacturing capability and qualified suppliers are scarce.

Manufacturing firms are always seeking better ways to mitigate risk when making decisions related to the purchase of goods and services. These decisions are quite complex and require decision makers to consider several inputs. In addition to price, considerations must be made regarding the capabilities of the suppliers as well as the probability that the goods and services are delivered on-time and meet quality and design specifications. Firms that produce standard high volume low value products (i.e., consumer electronics, household appliances, clothing, etc.) are challenged with managing multiple sources effectively while keeping prices low. On the other hand, manufacturers that produce relatively low volume high value products (i.e., aerospace, power plant construction, energy exploration, shipbuilding, etc.), may be constrained by the scarcity of suppliers with the requisite manufacturing capabilities to produce the product of interest. Furthermore, these industries typically have more stringent quality and regulatory requirements, which may narrow the supply base even further. With such few sourcing options, firms are often greatly exposed to the risks associated with a limited number of suppliers. This paper will focus on a proposed method to cost-effectively and proactively mitigate the risk associated with sourcing decisions in low volume high value supply chains.

Airliner manufacturing is one example of a low volume high value supply chain. In 2014, one report noted that since the start of manufacturing in 2007, Boeing had manufactured 228 [5] of their 787 Dreamliner aircraft at an average unit price of $258 million [6]. As of 2011, Boeing's total expenditure on the 787 program was estimated at $32 billion [7]. Boeing utilized a global outsourcing model in the design and manufacture of the 787; the likes of which had never been seen before. The outsourcing model was viewed as a primary means to significantly reduce development lead times and costs. In 2001, at a Boeing Technical Excellence Symposium [8], Boeing engineers warned of potential quality problems with prime contractors as a result of the "hands-off" outsourcing model being deployed. Ultimately, the launch of the Boeing 787 was delayed by more than 3 years and had budget overruns on the order of billions of dollars [2].

According to Boeing, one 787 Dreamliner is manufactured from approximately 2.3 million parts and an overall supply base of 5,000 factories support the manufacture of their five primary airliners [9]. The combination of the overall investment, diversity and quantity of suppliers, volume of products, and severity of the impact of a delay illustrates the need to proactively and systemically approach risk mitigation in such a supply chain. Doing so in a quantitative manner enables businesses to make better risk-informed decisions cost-effectively.

The supply chain associated with the manufacture of low volume high value components can be complex and lead times of critical components can be on the order of many years. Further, the unit cost of some components can exceed one hundred thousand dollars. Due to the large size of the components - some can weigh several tons - and subsequently the fabrication and manufacturing capability required to fulfill design requirements, a limited number of global suppliers exist. The quality and regulatory requirements placed on suppliers within these industries also increase the complexity of decision making. Hundreds of suppliers may be used in the assembly of an airline or in the construction of a nuclear power plant. In summary, suppliers with requisite capabilities are scarce, supplier development and order fulfillment lead times are long, and supply chain failures can have a significant impact on delivery, which can result in legal and financial ramifications. One estimate places the cost of delay in construction of a nuclear power plant at $2 million per day [10]. As a result, supplier selection and proactive risk mitigating activities are critical to ensure that suppliers deliver on time. Failing to implement such an approach proactively can be costly and time consuming.

As enterprise resource planning and manufacturing execution systems have improved, firms have become more objective with planning and scheduling decisions. Likewise, site selection, inventory stocking levels, and transportation decision models have become more sophisticated within supply chains. However, a gap in common industry practice still exists with respect to providing timely and cost-effective risk interdiction activities. As a result of the regulatory scrutiny on low volume high value industries producing critical components, these interdiction strategies are typically focused on compliance to regulator standards and not necessarily or specifically targeted to the performance of suppliers. Although compliance to regulations is vital, doing so does not ensure efficient or cost effective risk mitigation. Furthermore, the use of quantitative decision making instruments that consider the cost-risk tradeoff is scarce.

This paper provides a methodology to solve the problems associated with quantitatively assessing risk, selecting suppliers, and developing risk interdiction plans within a low volume high value supply chain. In doing so, we model a product's bill of material and subsequent supply chain in the form of a fault-tree. Unreliability measures are calculated and evaluated. Alternate sourcing options are evaluated on the basis of a tradeoff between risk reduction and the cost of implementing the mitigating actions. Examples of alternative options include redundant suppliers, improving existing suppliers, selecting higher performing suppliers, and combinations thereof.

1.2 Related Literature

A wide body of literature is available in the area of risk response and primarily focuses on redundancies, safety stock and inventory buffers, auditing, management intervention, and other strategies to hedge the consequences of a risk being realized [11]. However, opportunities exist in the areas of (1) assessing risk sources, (2) defining risk and consequences, (3) identifying risk drivers, and (4) mitigating risks[1]. As a result, instruments that model these areas associated with risk prevention are scarce as noted in several literature surveys [12, 13, 14, 15].

Researchers have analyzed supply chain risk management extensively from a qualitative point of view [16]. In their agenda for future research in the field, Juttner et al.[1] proposed a basic construct for supply chain risk management and noted needs for more practical approaches to risk assessment, a supply chain and industry-specific approach, better approaches for managers to identify risk drivers, and processes to guide trade-off decision making between risk reduction and mitigation costs. Likewise, several authors have proposed strategic frameworks and approaches to supply chain risk management [16, 17, 1, 18, 19, 11, 20] and some have focused specifically on mitigating such risks [21, 22, 23, 24, 25]. However, empirically based published work in the area remained sparse until recently and approaches have varied [26, 17]. In a review of quantitative models for managing supply chain risks, Tang [27] suggests that it is appropriate to use cost or profit as a means to evaluate options for managing operational risks and the usefulness of "back-up" suppliers. Furthermore, he discusses demand management, product management, and information management strategies. Toward the goal of developing an approach that minimizes cost as a means to evaluate options, Aqlan and Lam [28] propose a model to maximize risk reduction under budgetary constraints using bow-tie analysis. However, the authors use expert opinion as the basis for the likelihood and impact of the supply chain risks.

In practice, decisions related to supplier selection are often unstructured [29]. A variety of multi-criteria decision making approaches have been studied with respect to supplier selection and envelop several factors in the categories of quality, cost, delivery and service [30]. Other research incorporates order quantities and capacity constraints into the supplier selection decision making process [31, 32]. Methods include the analytical hierarchy process, goal programming, data envelopment, fuzzy set theory, genetic algorithms, and others [33, 34, 35, 36, 37, 38, 39, 40]. However, consideration for the impact on business objectives is lacking [41].

The area of supply chain disruption has been studied extensively. Blackhurst et al. [42] identified discovery, recovery, and redesign as the three primary areas crucial to managing supply chain disruptions. Among other conclusions, the authors point out that tools are needed to establish a regular system of supply chain disruption predictability and that dynamic or real-time measures are important.

Disruptive threats such as terrorism [43, 44], natural disasters [45], sourcing decisions [46], demand [47, 48, 49], and others are discussed in the literature as well as strategic frameworks and supply chain design methodologies [50, 51, 52, 53, 54] by which to manage and mitigate those threats. Work by researchers such as Snyder [55] and Cui [56] present models that consider risk in facility location as a method of risk management within supply chains. Inventory buffers [57, 14, 50, 54] and product mix [58] are also discussed as mitigating strategies against disruptions. Lastly, the empirical data resulting from the consequences of environmental disruptions such as the earthquake and tsunami that struck Japan in 2011 have been studied and models developed [59, 60].

Fault-tree analysis was originally developed by Bell Telephone Laboratories to evaluate the launch control system of the Minuteman Missile in 1961 [61, 62]. The method is objective and resolves highly complex systems into a prioritized set of causes leading to the top event (failure). Fault-trees are helpful in analyzing different ways in which a particular failure can occur and the probability of its occurrence [63, 64]. Since its inception, fault-tree analysis has become an accepted means for understanding hazards and failures associated with complex systems. However, the specific application to risk identification and interdiction within a supply chain is scarce. Klimov and Merkuryev [65] propose a quantitative approach to supply chain risk identification using a combination of reliability theory and simulation. However, their approach results in the probability of survival for the supply chain being studied for a specified period of time.

Traditionally, the application of fault-tree analysis focuses on process or product failures with the purpose of identifying safety or reliability issues within the system being studied [62, 66, 67, 68, 69, 70, 71, 72, 73, 74] or may reference an element of the supply chain as part of the larger system being studied as an event within the fault-tree [75]. Other authors [22, 11, 19, 76] note fault-tree analysis as a tool for risk analysis within a supply chain; however, do not develop the concept in great detail. Where fault-trees have been used to identify risk within a supply chain, the events that may occur within the supply chain are represented in aggregate and not developed to the level of detail of individual suppliers within the network [77, 78, 79, 28]. For example, Yuhua and Datao incorporate the physical means by which an oil pipeline may fail subsequently leading to a disruption in the oil and gas transmission industry, but do not include an assessment of other factors that may cause a supply chain disruption. Volkanovski et al. use a similar approach in their assessment of power system transmission reliability. In their assessment of drinking water distribution systems, Lindhe et al. take a slightly different approach using the categories of failure within three subsystems to illustrate supply failures in terms of quantity as well as quality. Aqlan and Lam propose the use of fault-tree analysis and event-tree analysis as part of bow-tie analysis, but do not construct specific fault-trees. Often and especially when empirical data is not available, judgmental assessments [76] are made to estimate failure rates and probabilities when fault-tree analysis used in supply chain risk mitigation. This can lead to decisions that are less transparent to management and can be based on opinions rather than facts. Further, using surveys and interviews to estimate the necessary data can be time consuming.

Fault-tree analysis is a well-known tool for quantifying and mitigating risk. Some people have applied fault-tree analysis to supply chains. However, there are some gaps related to the manner in which the fault-tree is constructed and the data used in analyzing the fault-tree. In this paper, we seek to develop an approach that closes these gaps by generating a fault-tree based on information that is readily available to analysts such as bill of materials and historical data that describes supplier performance. An approach like this allows a user to be explicit about defining the fault-tree events and probabilities, making the fault-tree itself more transparanet. Toward this end, we present a method for constructing a fault-tree based on a critical component's bill of materials that represents the risks associated with individual suppliers within a supply chain using historical data as a basis for unreliability measures. Such an approach lends itself to being automated and results in more timely decision making.

1.3 Contributions

The approach described herein proposes a new application of fault-tree analysis and in doing so provides a structured approach to represent the risks associated with sourcing decisions and specifically supplier selection. The methodology is based on empirical data sets that represent supplier performance and provides practitioners a decision support methodology to assist in supplier selection and make trade-offs between risk reduction and the costs associated with reducing such risks. Additionally, the output enables effective and proactive risk mitigation actions to be deployed cost effectively to suppliers with the greatest risk exposure across the company's aggregate supply chain. Specifically, this paper builds upon previous work in the areas of fault-tree analysis and supply chain risk mitigation by making the following main contributions. (1) A new methodology to formulate a fault-tree using the bill of materials of a low volume high value product being manufactured is demonstrated and subsequently utilized to quantify risk (unreliability) within the firm's supply chain. The data used to formulate the fault-tree is based on real-world scenarios and hypothetical on-time delivery data that is readily available to most firms. (2) A quantitative approach is employed to model the trade-off between risk reduction and the investment required to mitigate risks within the supply chain being studied. The development of time functions and subsequent costs are computed and subsequently combined with the results of the fault-tree analysis to provide the sourcing practitioner a methodology for risk-informed, cost-effective decision making. (3) A set of computational experiments in the form of simple scenarios provides results for decision makers to better understand the tradeoffs between risk reduction and total risk mitigation costs.

2 Problem Description

The purpose of the methodology described is to compute supply chain risk using fault-tree analysis and subsequently model alternative decisions in order to take better risk-informed actions regarding supplier selection and cost effective risk mitigation. In order to explain this methodology, we divide its formulation into two stages: (1) fault-tree formulation and (2) risk mitigation activities, which are described in greater detail in the sections that follow.

In its basic form, a supply chain is a system of firms connected to one another through relationships and physical transportation networks. Specifically, as Christopher [80] points out, a supply chain is a "network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services delivered to the ultimate consumer." Fault-tree analysis is a well-known method to analyze the reliability of systems and translates physical systems into a structured logic diagram, in which certain specified causes lead to one specific top event of interest [81]. Thus, our methodology is based on the ability to represent the system of firms and products being sourced from those firms within a supply chain as a fault-tree in the same way that someone may analyze the reliability of a nuclear power plant or chemical processing facility by analyzing the underlying components and systems.

2.1 Fault-Tree Formulation

In a fault-tree, the main failure event of interest is called the top event [82]. For the purposes of the approach described in this paper, the top event in the fault-tree represents the probability that a product will not be delivered on-time as the result of subsequent failures by suppliers of goods and/or services within the supply chain to deliver on-time. From the top event, the fault-tree is developed into intermediate and basic events and is based on the bill of material structure of the product being studied.

In this paper, we use the term *unreliability* to describe a supplier's failure to deliver a given product or service on-time. Specifically, unreliability is defined as the inability for a supplier to perform as intended (i.e., deliver on-time) for a specified period of time [83]. In other words, unreliability ($F(t)$) is the probability that the system experiences at least one failure during a specified time period, which for this paper is within the interval $[0, t]$ where $t = 52$ weeks. Reliability ($R(t)$) is the probability that the supplier makes all of its deliveries on time within the time interval and is related to unreliability through the relationship $R(t) + F(t) = 1$ (where $R(t) \in [0, 1]$, $F(t) \in [0, 1]$). Historical delivery data is used to compute the unreliability of delivering on-time and is discussed later.

Further, we assume that the failures that occur within the supply chain and that subsequently lead to the unreliability of delivering products and services on-time are instantaneous and repairable as opposed to unrepairable (i.e., catastrophic) in nature. We do not take into consideration the duration of time to get the event under repair back into working condition and leave these topics to explore in the future. As a result of these assumptions, the use of unreliability is appropriate.

In this paper, a thrust bearing is used to illustrate the concept (see Figure 1) and is representative of a low volume high value industry. However, the product selected could have been the electric motor assembly that houses the thrust bearing or in a more complex fashion, a product that utilizes a motor within its fabrication (i.e., an aircraft, a building, a ship, etc.). In that case, the motor would be shown as a sub-assembly on that product's bill of materials.

The thrust bearing, which is a common assembly used in the manufacture of electrical and mechanical devices is broken down into its main subcomponents - thrust shoes, brackets, leveling links, support rings. Each subcomponent is then subsequently decomposed into the most basic goods and services (hereafter referred to as "basic services") used in their respective manufacturing processes. The most elemental basic services that comprise the subcomponent (i.e., melt stock, casting, machining, etc.) are basic events within the fault-tree. These basic events combine to form intermediate events, which correspond to the subcomponents (i.e., thrust shoes, brackets, etc.) that make up the product being studied and are represented by the top event in the fault-tree. Each basic and intermediate event is described by the unreliability of the respective supplier chosen to provide the required service on-time. Specifically, $f_{ij}(t)$ represents the probability that the supplier has failed to deliver their respective service on-time within the interval $[0, t]$. For simplification, we will use the notation f_{ij} to describe the unreliability of supplier i to deliver service j hereafter; it is assumed that $t = 52$ weeks (one year).

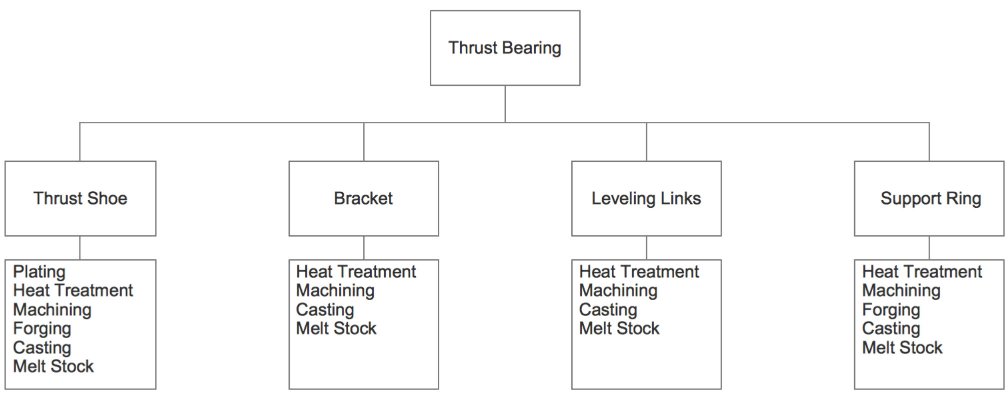

Figure 1: Thrust bearing bill of material.

After the product's bill of material has been deconstructed into basic services, suppliers are selected. For the thrust bearing example described above, the supply chain consists of seven ($i \in [1, 7]$) basic services sourced from 28 ($j \in [1, 28]$) independent suppliers. In the case studies presented later, we will introduce two additional suppliers whose data will be described further. Table 1 summarizes the basic services used to manufacture the thrust bearing.

Table 1: Thrust bearing basic services.

Basic Service	**Basic Service Index (i)**
Casting	1
Forging	2
Heat Treatment	3
Laboratory and Test	4
Machining	5
Melt Stock	6
Plating	7

Historical performance data associated with each supplier's ability to supply the respective basic service on-time is used to formulate the unreliability measure (f_{ij}) and is described in Equation 1. Table 2 summarizes the probability that each supplier fails to deliver the respective service on-time.

$$f_{ij} = 1 - \frac{\sum_{ij} x_{ij}}{\sum_{ij} y_{ij}} \tag{1}$$

where

f_{ij} = annualized unreliability for basic service i sourced from supplier j

x_{ij} = annualized units of basic service i delivered on-time by supplier j

y_{ij} = units of basic service i expected annually by supplier j

$f_{ij} \in [0, 1]$

$x_{ij} \in [0, 1]$

$y_{ij} \in [0, 1]$

$i \in [1, n]$

$j \in [1, m]$

n = total number of basic services within supply chain

m = total number of suppliers within supply chain

Table 2: Combined basic service and supplier unreliability data.

Basic Service	**Basic Service Index** (i)	**Supplier** (j)	**Unreliability** (f_{ij})
Plating	7	1	0.0134
Laboratory and Test	4	2	0.0337
Machining	5	3	0.0247
Casting	1	4	0.0523
Forging	2	5	0.0889
Laboratory and Test	4	6	0.0260
Heat Treatment	3	7	0.0133
Machining	5	8	0.0125
Casting	1	9	0.1215
Laboratory and Test	4	10	0.0420
Heat Treatment	3	11	0.0150
Machining	5	12	0.0125
Casting	1	13	0.1263
Laboratory and Test	4	14	0.0393
Heat Treatment	3	15	0.0189
Machining	5	16	0.0224
Casting	1	17	0.0968
Forging	2	18	0.0820
Heat Treatment	3	19	0.0282
Melt Stock	6	20	0.0092
Laboratory and Test	4	21	0.0142
Melt Stock	6	22	0.0123
Laboratory and Test	4	23	0.0417
Melt Stock	6	24	0.0251
Laboratory and Test	4	25	0.0327
Melt Stock	6	26	0.0212
Laboratory and Test	4	27	0.0421

In its basic form, the fault-tree is a logic diagram that depicts events that must occur in order for subsequent events to occur. A fault-tree is composed of entities known as gates that serve to permit or inhibit the passage of fault logic up the tree and show the relationships of events needed for a higher event (output of the gate) to occur [84]. Since gates relate events within the fault-tree in the same way as Boolean operations, the rules of Boolean Algebra apply. Two types of gates are used in this paper - AND gates and OR gates. AND gates represent the intersection of the events attached to the gate and are used to demonstrate situations whereby redundant suppliers are employed. The output failure associated with an AND gate occurs only if all of the input events to that gate fail; whereas, if at least one of the events that are an input to an OR gate fail, the output event of that gate also fails. OR gates represent conditions where only one supplier is supplying a given basic service and if that supplier should fail to deliver on-time, a disruption to the supply chain occurs resulting in a failure to deliver the final product (i.e., trust bearing) on-time.

Equations 2 and 3 describe the formulae used in the calculation of OR and AND gate probabilities, g_k^{OR} and g_k^{AND} respectively. By assuming that basic and intermediate input events and the respective unreliabilities are independent of one another, we are able to utilize the bottom-up gate calculation method in calculating the top-event failure rate. We achieve independence of events by assuming that each supplier of one basic service is independent of all other suppliers of basic services within the supply chain. Further, failures to deliver services on-time within the supply chain are exclusive to individual suppliers and are not correlated between suppliers. For example, a catastrophic event that impacts a geographic region and includes multiple suppliers is not considered here and is left for future research. Without these assumptions, the minimum cut set approach for analyzing fault-trees is more appropriate.[85]

$$g_k^{OR} = 1 - \prod_{i,j}(1 - f_{ij}) \tag{2}$$

$$g_k^{AND} = \prod_{i,j} f_{ij} \tag{3}$$

where

g_k^{OR} = the gate unreliability of OR gate k

g_k^{AND} = the gate unreliability of AND gate k

$k \in [1, q]$

q = the total number of gates within the fault-tree

$k = 1$ for top event gate

The resulting output of the fault-tree is the system unreliability (F_S) , which corresponds to the top gate calculation in the fault-tree ($k = 1$) and corresponds to the probability that the product being studied (i.e., thrust bearing) will not be delivered on-time. Subsequently, the system-level measures are used to determine the effect of making changes to lower level events within the fault-tree, which correspond to sourcing decisions within the supply chain. Further, we consider the costs associated with these decisions in relation to their favorable or unfavorable impact on the system level risk. In the sections that follow, we demonstrate this generalized concept through illustrative examples, but first we discuss the cost basis for formulating the risk-mitigation decisions using the proposed methodology.

Figure 2 illustrates the baseline case of the fault-tree that describes the supply chain associated with the manufacture of a thrust bearing and Table 3 contains the corresponding gate unreliability data. All gates within this scenario are represented by *OR* gates and result in an overall system unreliability (F_S) of 0.6692. Initially, there is no redundancy in this system. Later, we introduce redundancy in the form of multiple suppliers for a given commodity using *AND* gates. Using the aforementioned definition of unreliability, this supply chain has a 66.92% probability that the system will experience at least one failure to deliver on-time within a one-year time frame.

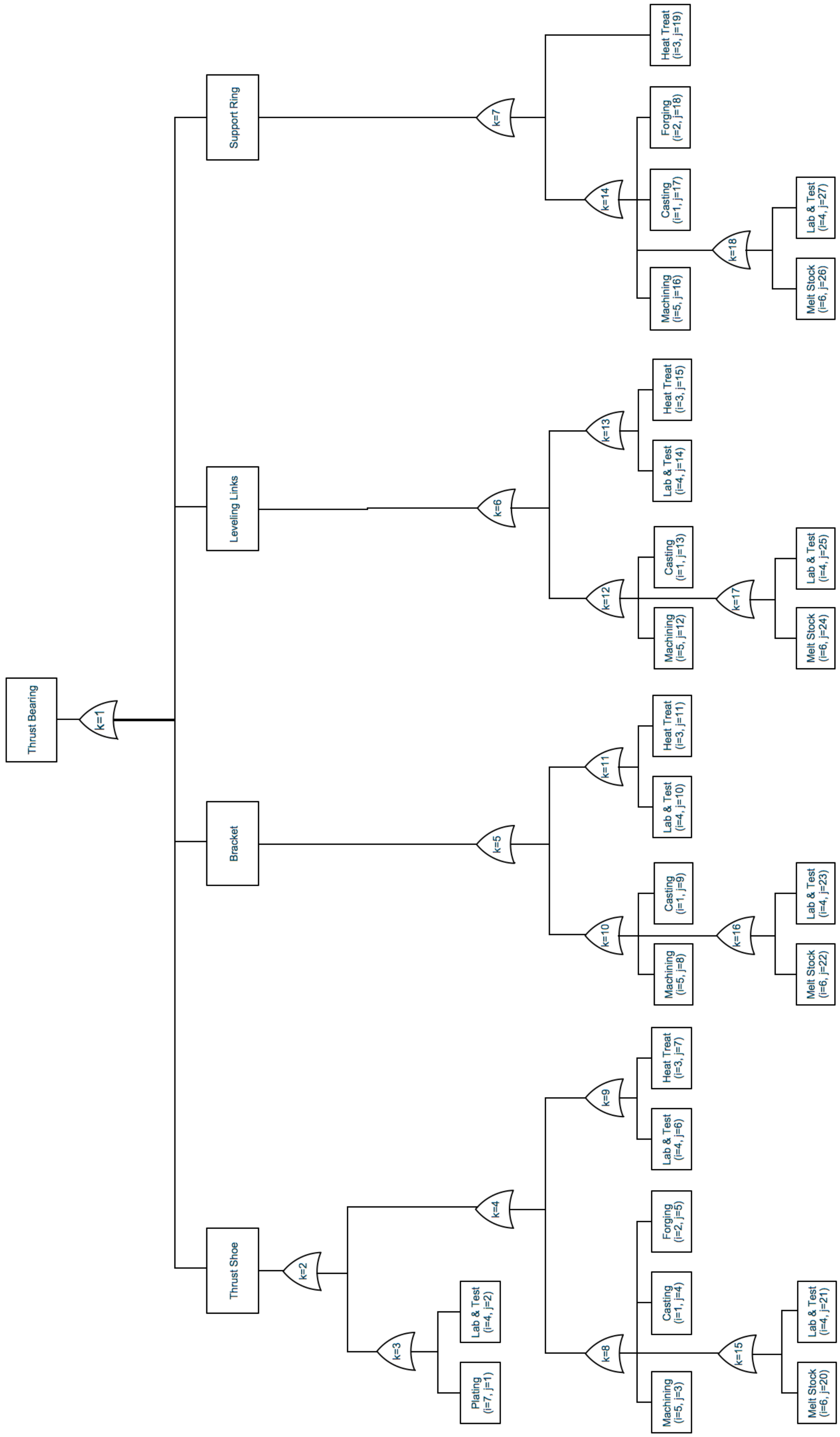

Figure 2: Baseline fault-tree.

Table 3: Baseline gate unreliability results.

Gate Number (k)	**Gate Type**	**Gate Unreliability (g_k^{OR}, g_k^{AND})**
1	OR	0.6692
2	OR	0.2463
3	OR	0.0466
4	OR	0.2094
5	OR	0.2250
6	OR	0.2331
7	OR	0.2615
8	OR	0.1774
9	OR	0.0389
10	OR	0.1788
11	OR	0.0563
12	OR	0.1864
13	OR	0.0574
14	OR	0.2400
15	OR	0.0233
16	OR	0.0535
17	OR	0.0570
18	OR	0.0624

In order to demonstrate the efficacy of the approach described, we have provided a simplified model and base the model on the following simplifying assumptions:

1. **Independent Events**. The events used to build the fault-trees presented are assumed to be independent. As a result, the success or failure of one supplier to deliver a product or service on-time is independent of any other success or failure within the fault-tree. We achieve this by assuming that all products and services are sourced from different suppliers. In doing so, we are able to use the simplified gate-based approach to calculate the top event failure rate and probability.

2. **Repairable System**. A repairable system is one in which conditions exist such that a failure, when occurring to a basic event, is announced, quickly detected and the system continues to operate with a known failure [82]. In the context of this paper, we have chosen to treat the supply chain being studied as a repairable system mostly because any individual supplier would most likely continue operations throughout the failure to deliver. This is practical since for low volume high value supply chains, the switching cost is significant. Although we have chosen to note the system as repairable, there is no practical impact to our analysis since we have chosen to utilize gate calculations and have not used minimum cut sets in our analysis.

3. **Unreliability**. Unreliability is chosen as the parameter to assess risk within a supply chain more specifically and is defined as the probability the fault event occurs during a specified time interval, usually 0 to t [82]. This parameter is appropriate given that unreliability is used to describe the probability that the product will be delivered late during a one year time horizon. The unreliability parameter alone does not account for the effect that the failure has on the length of the delay caused by the disruption and is of greater consequence when analyzing the effectiveness of redundant cases (AND gates) within the system.

2.2 Risk Mitigation Costs

In addition to the calculated risk metrics that result from the fault-trees (e.g., unreliability), we have also chosen to introduce cost measures to help the analyst compute the cost effectiveness of various risk mitigating actions. Four cost-based decisions to mitigate risk within the supply base are considered and are based on the time associated with executing the respective activity. The time functions presented are a function of the supplier's unreliability or change (improvement) in unreliability. The time functions were derived using a line-of-best-fit approach and based on data sets from industry examples. Equations 4, 5, and 6 describe the time to (1) improve a supplier (Equation 4), (2) onboard a supplier (Equation 5), and (3) provide oversight at a supplier (Equation 6). The appropriate time function is applied to each of four potential decisions to mitigate risk: (1) add a new supplier, (2) replace the existing supplier with an improved supplier, (3) improve the existing supplier, and (4) provide oversight for a supplier. An hourly rate of $104 per hour is used to calculate the associated costs from each time function and is considered representative of the fully burdened rate for an Engineer in the United States [86] for a low volume high value industry. The models are annualized for comparison purposes and travel costs and other expenses are not included in the cost estimate. Table 4 summarizes the time functions used for each of the risk mitigating decisions and demonstrates the cost calculation for each. These functions are subsequently used to predict the costs associated with the aforementioned risk mitigation activities within the supply chain.

$$t_{ij}^{improve} = 4278u^{1.84}, \tag{4}$$

$$t_{ij}^{onboard} = 43e^{3.83f_{ij}}, \tag{5}$$

$$t_{ij}^{oversight} = 23e^{2.64f_{ij}}, \tag{6}$$

$$u = 1 - \frac{f_{ij,S_2}}{f_{ij,S_1}} \tag{7}$$

where:

$t_{ij}^{improve}$ = time (hours) invested annually to improve a supplier,

$t_{ij}^{onboard}$ = time (hours) invested annually to onboard a supplier,

$t_{ij}^{oversight}$ = time (hours) invested annually to provide oversight to maintain supplier,

u = unreliability improvement ratio from s_1 to s_2,

$e \approx 2.71828$

s_1 = initial state of unreliability of supplier j to deliver basic service i,

s_2 = improved state of unreliability of supplier j to deliver basic service i,

$f_{ij,S_1} > f_{ij,S_2}$

Table 4: Costs as a function of time for risk mitigation actions.

Risk Mitigating Action	**Cost Calculation**
Add a new supplier	$c_{ij}^{onboard} = \$104 * t_{ij}^{onboard}$
Replace existing supplier with an improved supplier	$c_{ij}^{onboard} = \$104 * t_{ij}^{onboard}$
Improve existing supplier	$c_{ij}^{improve} = \$104 * t_{ij}^{improve}$
Provide supplier oversight to maintain performance	$c_{ij}^{oversight} = \$104 * t_{ij}^{oversight}$

Using Equations 4, 5, and 6 in combination with Table 4, costs to mitigate risk are estimated. For example, reducing the unreliability (i.e., improve reliability of on-time delivery) of a casting supplier (j = 13; see Table 2) from 0.1263 to

0.0947 (25% reduction) results in an improvement ratio (Equation 7) of $u = 0.25$. Using Equation 4, the time required to reduce this particular casting supplier's unreliability by 25% is 334.3 hours and subsequently costs the firm \$34,762 using the information described in Table 4. If that same casting supplier ($j = 13$) was replaced by a casting supplier with an unreliability of 0.0947, the time to onboard (Equation 5) the new supplier is 61.8 hours, which corresponds to a cost of \$6,428. Similarly, using Equation 6, implementing additional oversight activities at the existing casting supplier ($f_{1,13}$) to maintain their current performance results in an estimated time commitment of 32.1 hours and corresponds to an annual cost of \$3,339. In contrast, adding a redundant supplier with equivalent unreliability as the initial casting supplier ($f_{1,13} = 0.1263$) costs the firm approximately \$7,254 (69.8 hours). Comparing the aforementioned risk mitigation options solely based on cost, the least expensive solution is to provide additional oversight at the existing supplier, which is standard industry practice. However, this is a short-sighted approach since the impact of the decision to the overall improvement (reduction) to the reliability (unreliability) of the supply chain is not considered when compared against the other more costly alternatives. This concept is explored further in the sections that follow by combining the costs of mitigation activities with the impact of those activities to risk reduction in the supply chain using fault-tree analysis.

3 Risk Mitigation Scenarios

This section describes case studies to illustrate contributions of this work and demonstrate how sourcing professionals may use such an instrument to determine the scenarios, risks, and subsequent risk mitigation plans prior to order placement with the intent of selecting suppliers and combinations of suppliers that optimize their supply chain portfolio. In the course of building each simple scenario, we introduce a second supplier for one commodity, an improved supplier for one commodity, and an improved second supplier for one commodity. Next, we analyze the effect that each of these scenarios has on the system. In each case, we maintain the assumption that all sources of supply are independent, that a new supplier can begin producing in the same timeframe as an existing supplier, and that initial demand is level-loaded between the two suppliers to hedge risk.

The case described by the fault-tree in Figure 2 is used as the baseline scenario. Table 2 includes the event data used as input to the fault-tree and is updated accordingly for each scenario discussed.

3.1 Scenario 1: Introduce a Second Equivalent Supplier

In this first scenario, we introduce a second casting supplier ($j = 28$) in the manufacture of the thrust bearing leveling links with an equivalent unreliability ($f_{1,13} = f_{1,28} = 0.1263$) as the existing casting supplier ($j = 13$). Within the fault-tree, the two suppliers become inputs to a new gate ($k = 19$), which is an *AND* gate. We have selected to introduce a second source for this supplier and commodity combination because the existing casting supplier has the highest unreliability of any other supplier in the supply chain (0.1263). The addition of a second equivalent casting source results in a total system unreliability of 0.6274 ($F_S = 0.6274$) compared to the baseline case where $F_S = 0.6692$ and corresponds to an approximate 6.2% reduction in the risk of the supply chain. However, the action of adding an equivalently unreliable supplier comes at a cost of \$7,254 (Equation 5, Table 4). Table 5 includes the data associated with the second casting supplier. Figure 3 shows the section of the baseline fault-tree that has been updated as a result of the addition of the second casting source and Table 6 contains the corresponding data. All other aspects of the fault-tree architecture remain the same.

Table 5: Second casting source ($j = 28$) data table.

Description	**Basic Service (i)**	**Supplier (j)**	**Unreliability (f_{ij})**	**System Unreliability (F_S)**	**Mitigation Cost**
Casting	1	28	0.1263	0.6274	\$7,254

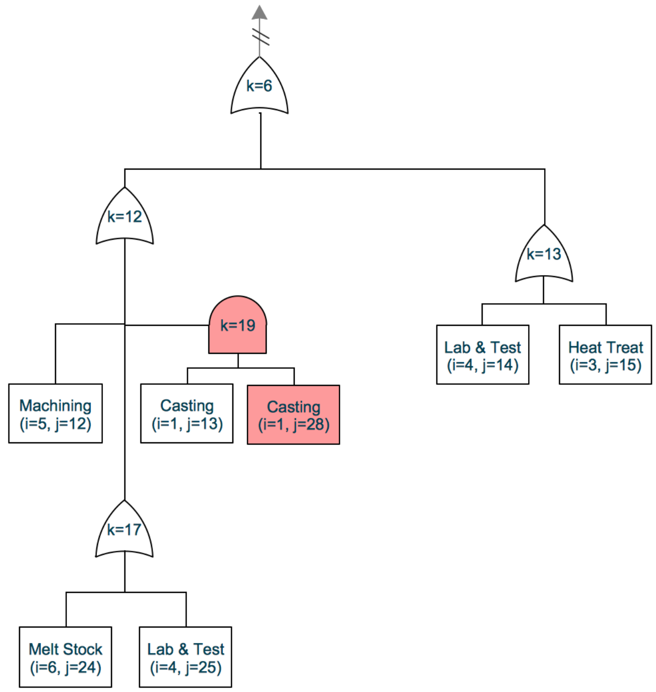

Figure 3: Modification to baseline fault-tree architecture for Scenario 1.

Table 6: Gate unreliability results updated for Scenario 1.

Gate Number (k)	**Gate Type**	**Gate Unreliability (g_k^{OR}, g_k^{AND})**
1	OR	0.6274
2	OR	0.2463
3	OR	0.0466
4	OR	0.2094
5	OR	0.2250
6	OR	0.1363
7	OR	0.2615
8	OR	0.1774
9	OR	0.0389
10	OR	0.1788
11	OR	0.0563
12	OR	0.0837
13	OR	0.0574
14	OR	0.2400
15	OR	0.0233
16	OR	0.0535
17	OR	0.0570
18	OR	0.0624
19	AND	0.0160

3.2 Scenario 2: Improve (or Replace) the Existing Supplier

In the second scenario, instead of utilizing a second source to reduce risk with the highest risk supplier, we instead decide to work with the same casting supplier ($j = 13$) to improve their performance by 25%. As a result, the fault-tree architecture remains the same as the baseline case (see Figure 2). However, the supplier's unreliability ($f_{1,13}$) is reduced by 25% (from

0.1263 to 0.0947). Table 8 shows the updated gate calculation results for Scenario 2. Using Equation 4 and the information contained in Table 4, improving the existing casting supplier comes with an annual cost of \$34,763. We will discuss the impact of these costs in the subsequent section and will see that the effects on the overall risk profile will remain the same as if we replaced the existing supplier with an improved supplier. However, the cost to develop a new, improved casting source ($f_{1,29} = 0.0947$) to replace the existing supplier is \$6,427 (Equation 5 and Table 4). Hereafter, we will reference the case when the existing supplier is improved as Scenario 2a and the case when the existing supplier is replaced as Scenario 2b when analyzing the associated costs. Table 7 includes the updated input data used in calculating the top event unreliability for the fault-tree associated with Scenario 2. Overall, the impact to the system is equivalent for Scenario 2a and Scenario 2b ($F_S = 0.6572$) and corresponds to an approximately 1.8% reduction in the overall system unreliability when compared to the baseline case ($F_S = 0.6692$).

Table 7: Improve (or Replace) existing casting source ($j = 13$) data table.

Description	**Basic Service (i)**	**Supplier (j)**	**Unreliability (f_{ij})**	**System Unreliability (F_S)**	**Mitigation Cost**
Casting	1	13	0.0947	0.6572	\$34,763
Casting	1	29	0.0947	0.6572	\$6,427

Table 8: Gate unreliability results updated for Scenario 2.

Gate Number (k)	**Gate Type**	**Gate Unreliability (g_k^{OR}, g_k^{AND})**
1	OR	0.6572
2	OR	0.2463
3	OR	0.0466
4	OR	0.2094
5	OR	0.2250
6	OR	0.2054
7	OR	0.2615
8	OR	0.1774
9	OR	0.0389
10	OR	0.1788
11	OR	0.0563
12	OR	0.1570
13	OR	0.0574
14	OR	0.2400
15	OR	0.0233
16	OR	0.0535
17	OR	0.0570
18	OR	0.0624

3.3 Scenario 3: Introduce a Second Improved Supplier

In the third scenario, we essentially combine the two previous scenarios to determine the effect on the system of introducing a second casting supplier ($j = 30$) with better performance than the initial casting supplier ($j = 13$). Like in Scenario 2, we assume the improvement is equal to 25%. The fault-tree architecture remains the same as in Scenario 1 with modification to the unreliability data and resulting gate calculations (see Figure 4 and Table 10). Similar to Scenario 1, costs are incurred by bringing on this new supplier. However, since the supplier ($j = 30$) has a track record of 25% improvement performance over the initial supplier ($j = 13$), the on boarding and development cost is less (\$6,427). The data used in fault-tree calculations for Scenario 3 are included in Table 9. Overall, the risk mitigating actions taken in Scenario 3 result in an approximately 6.5% reduction in system unreliability.

Table 9: Improved second casting source data table.

Description	Basic Service (i)	Supplier (j)	Unreliability (f_{ij})	System Unreliability (F_S)	Mitigation Cost
Casting	1	30	0.0947	0.6259	$6,427

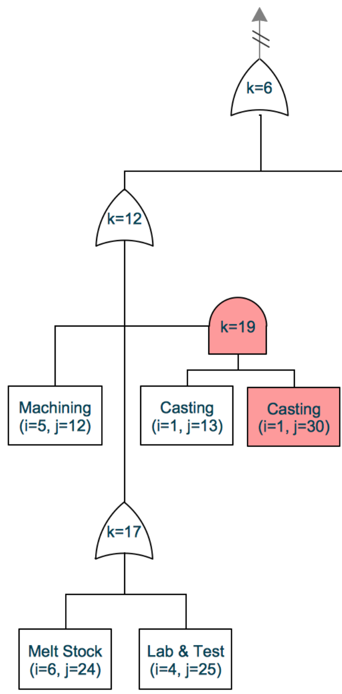

Figure 4: Modification to baseline fault-tree architecture for Scenario 3.

Table 10: Gate unreliability results updated for Scenario 3.

Gate Number (k)	Gate Type	Gate Unreliability (g_k^{OR}, g_k^{AND})
1	OR	0.6259
2	OR	0.2463
3	OR	0.0466
4	OR	0.2094
5	OR	0.2250
6	OR	0.1328
7	OR	0.2615
8	OR	0.1774
9	OR	0.0389
10	OR	0.1788
11	OR	0.0563
12	OR	0.0800
13	OR	0.0574
14	OR	0.2400
15	OR	0.0233
16	OR	0.0535
17	OR	0.0570
18	OR	0.0624
19	AND	0.0120

3.4 Summary

Table 11 includes the output of the fault-trees constructed for each of the scenarios presented and the corresponding estimated costs of mitigating the associated risks. Figure 5 illustrates the trade-off between the reduction in risk for each scenario from the baseline case and the corresponding cost to mitigate the risk.

According to the cost model presented, oversight for the existing casting supplier ($f_{1,13} = 0.1263$) costs the firm \$3,339 annually and is only assumed to maintain the supplier's current level of unreliability. As a result, the oversight carrying cost of \$3,339 is included in the total mitigation costs of Scenarios 0, 1 and 3. Often, low volume high value industries like those described above use oversight as the primary means in providing a sense of assurance in mitigating risks. However, this oversight is primarily compliance-based and targets only whether or not the firm is adhering to their standard operating procedures and does not address the effectiveness or efficiency in the firm's ability to do so. As a result, oversight activities do not serve to reduce the firm's unreliability, but at best can only be expected to maintain the current state. Any improvements yielded as a result of oversight are only related to correcting deficiencies at the firm regarding compliance to their standard operating procedures.

Table 11: Summary of results.

Scenario	**Decision**	**System Unreliability (F_S)**	**Scenario Mitigation Cost**	**Total Mitigation Cost**	**System Unreliability Improvement**
0	Baseline	0.6692	\$3,339	\$3,339	–
1	Introduce a Second Equivalent Supplier	0.6274	\$7,254	\$10,593	6.2%
2a	Improve the Existing Supplier	0.6572	\$34,763	\$34,763	1.8%
2b	Replace the Existing Supplier	0.6572	\$6,427	\$6,427	1.8%
3	Introduce a Second Improved Supplier	0.6259	\$6,427	\$9,766	6.5%

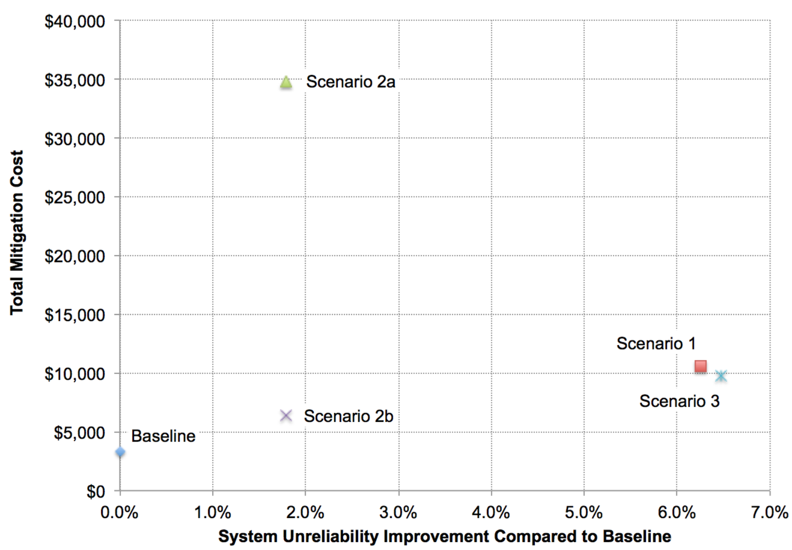

Figure 5: Tradeoff between risk reduction and mitigation costs for reducing risk.

Introducing a second equivalently performing casting supplier (Scenario 1) provides a 6.2% improvement in the system reliability. However, doing so will cause the firm to outlay an additional \$7,254 in mitigation costs beyond the cost of maintaining the existing supplier (\$3,339) for a total mitigation cost of \$10,593. Improving the existing supplier (Scenario 2a) or replacing the existing supplier with an improved supplier (Scenario 2b) provides the least reduction in the supply chain's risk, 1.8%, and comes with costs of $34,763 and $6,427 respectively. The scenario that introduces a second, yet improved, casting supplier (Scenario 3) appears to provide the greatest reduction in the risk within the supply chain (6.5%) and at an equivalent cost as replacing the existing supplier with an improved supplier ($6,427). However, since in this scenario the existing supplier will remain, their carrying cost must be considered. Thus, the total mitigation cost for Scenario 3 is $9,766. Even after the total cost of mitigation is considered, adding a second improved casting supplier provides greater unreliability improvement (6.5% vs. 6.2%) at less cost ($10,593 vs. $9,766) than introducing a second equivalently unreliable casting supplier as the original.

In summary, since Scenarios 1 and 2a are more expensive when compared to Scenarios 2b and 3, they would eliminated from consideration by decision makers on the basis of cost as risk mitigation strategies. Although Scenario 2b is less expensive than Scenario 3, the relative risk reduction is minimal by comparison. As a result, Scenario 3 should be chosen as the risk mitigation strategy.

4 Conclusions and Future Work

In this paper we presented a new application for fault-tree analysis that has the potential of providing sourcing professionals an instrument to build scenarios and make better informed decisions. In doing so, we studied the supply chain of a thrust bearing used in an application within a low volume high value supply chain. This type of supply chain provides one of the biggest opportunities to employ such an instrument due to the associated risks, long lead times, and value of the products being manufactured and constructed. We presented simple case studies to provide examples of how such an instrument could be beneficial and then analyzed the results.

Experiments using the methodology illustrated that introducing a redundant supplier with improved performance provided the greatest reduction in overall risk at a slightly lower total cost than adding an equivalently unreliable supplier. The assessment methodology allows the practitioner to quantitatively and objectively distinguish between seemingly similar options to reduce risk. Thus, less attractive options such as introducing a second equivalent supplier, improving the existing supplier, providing additional oversight at the existing supplier or replacing the existing supplier may also have been considered as effective at first glance, can be objectively analyzed using our method.

Several areas of future work are planned. The first entails the development of a software instrument that has the capability to perform the tasks outlined in this paper in an automated fashion. Such tasks include development of the fault-tree from the bill of material, calculation of failure rates and probability, and selection of an optimized scenario of risk reduction and cost under budgetary constraints. The second includes refinement and sensitivity analysis with regard to the underlying risk and cost data as well as the associated models used to produce the results presented here. Third, it would be interesting and useful to further explore several assumptions used in developing our model. For example, the approach presented assumes that the performance of a supplier is known at the time of decision-making. However, this may not be the case in practice such as when a supplier is new to the firm interested in sourcing product or rendering services from them. The relaxation of the independence assumption as well as the integration of risk severity and consequence into the methodology presented here is left for future research. Additionally, event dependence and the use of minimum cut set analysis in lieu of the simplified gate calculation approach employed in this paper would be useful areas to explore further. Lastly, consideration for unrepairable events, the unavailability of a supplier's services, and duration of delays due to failure and start-up will be considered.

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