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An Optimized Resource Allocation Approach to Identify and Mitigate Supply Chain Risks using Fault Tree Analysis

Michael D. Sherwin

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An optimized resource allocation approach to identify and
mitigate supply chain risks using fault tree analysis

By

Michael D. Sherwin

A Dissertation
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
in Industrial and Systems Engineering
in the Department of Industrial and Systems Engineering

Mississippi State, Mississippi

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2018

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mitigate supply chain risks using fault tree analysis

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Low volume high value (LVHV) supply chains such as airline manufacturing, power plant construction, and shipbuilding are especially susceptible to risks. These industries are characterized by long lead times and a limited number of suppliers that have both the technical know-how and manufacturing capabilities to deliver the requisite goods and services. Disruptions within the supply chain are common and can cause significant and costly delays. Although supply chain risk management and supply chain reliability are topics that have been studied extensively, most research in these areas focus on high volume supply chains and few studies proactively identify risks. In this research, we develop methodologies to proactively and quantitatively identify and mitigate supply chain risks within LVHV supply chains. First, we propose a framework to model the supply chain system using fault-tree analysis based on the bill of material of the product being sourced. Next, we put forward a set of mathematical optimization models to proactively identify, mitigate, and resource at-risk suppliers in a LVHV supply chain with consideration for a

firm's budgetary constraints. Lastly, we propose a machine learning methodology to quantify the risk of an individual procurement using multiple logistic regression and industry available data, which can be used as the primary input to the fault tree when analyzing overall supply chain system risk. Altogether, the novel approaches proposed within this dissertation provide a set of tools for industry practitioners to predict supply chain risks, optimally choose which risks to mitigate, and make better informed decisions with respect to supplier selection and risk mitigation while avoiding costly delays due to disruptions in LVHV supply chains.

Key words: Supply chain risk management, system reliability, fault tree analysis, multiple logistic regression, mixed integer programming, optimization

DEDICATION

To my children, Andrew and Kate. May you realize that with faith, hard work, a positive attitude, and an open mind all things are possible. I hope to always make you proud and can't wait to see what great things God has in store for you.

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I would first like to thank my wife, Becky. She has supported me without hesitation and served as my dedicated sounding board on more occasions than I could ever count. Words don't adequately describe how grateful I am for your support through this journey. You're my best friend. I am blessed to walk through life with you by my side.

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Next, I would like to thank the firm that provided information and actual data sets to conduct this research. The ability to apply the methods developed throughout this dissertation on problems facing industry provides additional efficacy to the approaches outlined.

Last, but certainly not least, I would like to thank Kennedy Brown who served as an undergraduate researcher and assisted me in setting up some of the data models as well as researching methods to convert fault trees to binary decision diagrams. I sincerely appreciate the help you provided.

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CHAPTER 1

INTRODUCTION

The act of coalescing risk-based decision inputs and subsequently making informed risk mitigating decisions within a firm is a complex activity. The information available is often qualitative, contained in silos within the organization, and requires extraordinary coordination and timeliness in order to mitigate risks before they occur. As a result, these decisions are made qualitatively and without regard for the overall system impact. The result is a reactive-based approach that focuses on resolving issues after they have occurred.

The objective of this research is to advance the state of the art with respect to quantitative risk identification, mitigation planning, and supplier selection within manufacturing supply chains and serve as a bridge for several academic communities. The methods developed as part of this research have practical applications within industry. Firms are constantly challenged with proactively reducing the risk exposure to their respective supply chains. However, the means of doing so in an efficient, integrated, quantitative, and effective manner is not standard practice. Although a significant amount of research has been published in the areas of Operations Research, Big Data, Supply Chain Risk Management, Reliability Engineering, and Systems Engineering, a gap exists where these areas intersect and specifically for low volume high value (LVHV) manufacturing supply chains

such as those used in the shipbuilding, aerospace, defense, and power plant construction industries. Merging and advancing the state of the art across these respective communities of research creates value in both academic and industrial settings. Ultimately, the benefits of deploying such a methodology has the potential to save firms millions of dollars annually. For example, the commercial nuclear power industry, which relies on LVHV supply chains, can experience costs on the order of \$2 million per day as the result of delays in new power plant construction [1].

1.1 Background and Motivation

The motivation for this research is rooted in more than 15 years of experience by the author across a variety of firms and industries. Whether large or small revenue, private or public, seasoned or start up, high or low volume, make-to-stock or make-to-order, companies struggle to operationalize data across silos. As a result of improved technology, the ability to collect data becomes easier. However, turning that data into information remains a challenge. As a result, firms often utilize weighted scoring methods and qualitative rankings to assess supplier risk. Although simple to deploy, these methods are not typically validated with respect to the effectiveness in improving risk management decisions nor do they have the resolution necessary to provide clarity to the decision making process [2].

We have chosen a LVHV supply chain as the focus of this research not only because of the author's experience working in the industry, but also because the industry provides a unique opportunity to examine a supply chain that has an intersection of challenges with respect to mitigating risks that other types of supply chains do not. Single sources of

supply, identifying the appropriate suppliers with the requisite capabilities, cost burdens associated with navigating regulatory requirements, large product manufacturing, low volume manufacturing, and make-to-order/design are attributes associated with many types of manufacturing supply chains. However, the supply chains associated with nuclear power plant construction face all of these challenges and associated risks simultaneously, which makes the industry an interesting focal point for this research. In 2014, the World Nuclear Association summarized the challenges facing the nuclear supply chain in three primary areas - economic, capability, and quality [3].

Economically, the production of nuclear electricity rivals and recently has been lower than that of coal and has been significantly less than gas historically. However, the costs associated with building a new nuclear power plant are significant and continue to increase. According to the Union of Concerned Scientists, the 75 new power plants constructed between 1966 and 1977 in the United States incurred an average overrun cost of 207%. In recent years, construction costs have risen much faster for nuclear power than for other options. [4]

Problematic designs, equipment delivery, personnel, construction, and commissioning are inherent risks that drive costs. In order to leverage newer technology, first-of-a-kind reactors are being built, which raise the risks even higher and exposes firms to delays while problems with the new technology are worked out. The effects ripple throughout the supply chain. Furthermore, because of the operational efficiencies of nuclear energy, countries are introducing nuclear power for the first time, which creates problems associated with the

inherent learning curve of the companies within the supply chains of taking on such an endeavor. [5]

Despite the economic challenges, approximately 295 new nuclear power plants were under construction or planned in 2014 introducing an estimated \$26 billion of international procurement per year [3]. The increase in demand, increase in complexity, shortage of skilled labor, and shrinking manufacturing capabilities globally has placed a significant demand on the firms comprising the supply chains tasked with building the new power plants. Companies that once provided the nuclear-quality equipment and materials used in the construction of existing nuclear power plants have either exited the industry or no longer exist. As a result, a gap exists in equipment and manufacturing capabilities and quality certifications within the industry. For example, at one time approximately 400 companies in the United States supplied components for nuclear power plants and 900 nuclear stamps (N-stamp), the certification provided by the American Society of Mechanical Engineers (ASME) that permits firms to supply certain nuclear materials and components, had been issued. Today, fewer than 80 suppliers and 200 N-stamp certifications exist [4].

This research aims to contribute to the current state of the art by answering the following questions while at the same time developing new techniques to assist supply chain professionals in making more proactive decisions to mitigate the risks associated with LVHV supply chains using industry available data:

1. How can a complex supply chain be organized and analyzed simply to assess risk?
2. What are the mitigation activities that should be undertaken to mitigate risk within the supply chain, simultaneously minimize risk, and at the same time achieve budgetary goals?

3. In advance of placing a purchase order, how can the reliability of a procurement be predicted and what are the significant factors that contribute to the reliability of the procurement?

Figure 1.1 provides an overview of the research, which is based on three primary areas associated with answering the aforementioned questions.

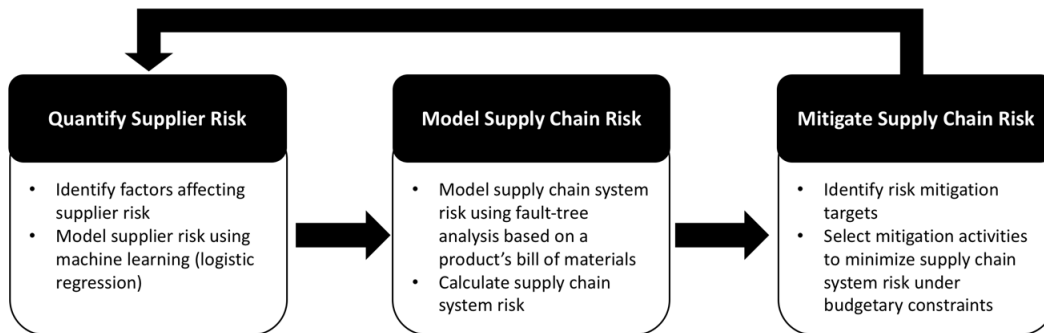


Figure 1.1: Overview of research.

First, we develop a methodology to represent a supply chain system as a fault tree and base it on a bill of materials. This allows us to simultaneously organize the supply chain into its respective tiers as well as analyze the overall reliability of the supply chain. Furthermore, this approach enables practitioners to simulate purchasing decisions proactively and assess the effect that the decisions may have with respect to risk. We demonstrate this concept through three industry-relevant case studies.

Next, building on the fault tree representation, we develop mixed integer programs to select optimal supplier mitigation activities to minimize risk within the supply chain

portfolio under budgetary constraints. We apply the concept to two LVHV supply chains in the nuclear power plant construction industry using industry-relevant data.

The third element of this research focuses on predicting the risk of a procurement. To do this, we develop a multiple logistic regression model using The American Production and Inventory Control Society's (APICS) Supply Chain Operations Reference (SCOR[®]) Model as a basis for our definition of reliability, which serves as the dependent variable in our model. Forty-two explanatory variables were selected based on industry experience and data available. Actual data from a firm within the nuclear power plant construction supply chain is used to build the model. We assess the performance and predictability of the model using standard metrics and analyze the explanatory variables for significance. We envision that the output models developed can serve as an input to the data utilized in modeling the supply chain system as a fault tree. However, we leave this area for future research.

The long-term goal of this research is to develop and implement a comprehensive software toolkit for supply chain professionals with the potential to integrate the three elements of the research described herein with one another and with a firm's existing data streams or as a stand-alone application. The toolkit has the potential to provide supply chain professionals a set of risk assessment and decision support tools that currently do not exist with regularity in industry. Example areas of supply chain planning where the future application could be implemented include, but are not limited to supply chain design activities, at the time of supplier selection, and for risk mitigation planning after purchase orders are placed. This dissertation serves as a foundation for that future work.

The remainder of this dissertation is organized as follows. The next section presents an overview of the relevant literature and discusses how this research contributes to filling current gaps. Subsequent chapters include a review of the specific literature associated with the topics discussed. Chapter 2 details the methodology associated with representing a supply chain system as a fault tree and discusses the usefulness of such an approach when applied to industry-relevant scenarios. Chapter 3 presents a optimization models to identify risk mitigating activities to minimize the unreliability of the supply chain being studied with consideration for budgetary constraints. The supply chains of two firms within the nuclear power plant construction supply chain are analyzed in Chapter 3. Chapter 4 develops a multiple logistic regression model based on industry data to predict the reliability of a procurement based on 42 explanatory variables. Lastly, Chapter 5 summarizes the conclusions of this research and recommends areas for future work. The Appendix includes a summary of the notation used within each Chapter as well as the detailed results generated from the content of Chapter 4.

1.2 Literature Review

This literature review provides a summary of the literature related to supply chain risk management, which lies at the core of the three areas discussed in this dissertation (see Figure 1.2). A more detailed review of the literature pertaining to the areas discussed are contained within the respective chapters of the dissertation that follow.

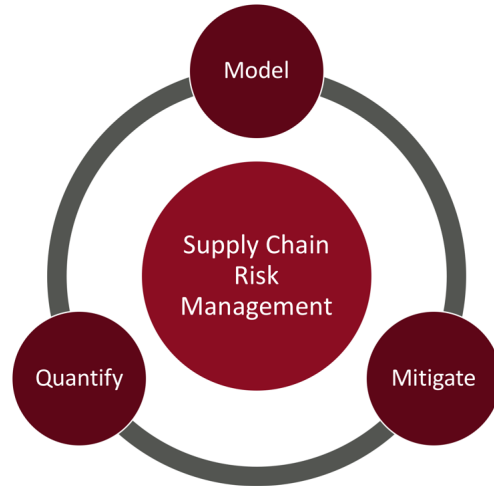


Figure 1.2: Topics of research outlined in this dissertation.

In 2003, Juttner et al. noted that supply chain risk management was in its infancy and outlined an agenda for future research in four primary areas: 1) assessing the risk sources for the supply chain, 2) defining the risk concept and adverse consequences, 3) identifying the risk drivers of the supply chain strategy, and 4) mitigating risks for the supply chain [6]. In the time since, a great deal of research has been applied to the field of supply chain risk management [7]. Between 1978 and 2003, an average of five papers per year were published in the area of supply chain risk modeling compared to an average of 44 papers per year in the time since [7]. Supply chain risk has also increased as a result of supply chains becoming more complex due to an increase in global sourcing and “leaning-down” [8]. In addition, the sources of risk to a supply chain have increased in complexity. However, much of what has been published in the literature focuses on a specific function or a part of a supply chain and does not consider the entire supply chain as a portfolio [9].

Our research aims to model supply chain risk across the supply chain by viewing the supply chain as a system and schematically as a fault tree. By taking this approach, we are able to overlay models that propose activities to mitigate risks. In addition, we propose models that assess the sources of risk as well as identify the drivers of those risks. Recently, some authors have proposed that the cross-fertilization of concepts, tools, and theories provides a pathway to advance the area of supply chain risk management modeling research [10]. Our research follows this theory and brings together the areas of modeling (logistic regression), optimization (mixed integer programming), and fault tree analysis in order to provide the supply chain practitioner with a more robust quantitative decision making toolbox to manage and mitigate risks.

Although several authors have proposed methods to quantify supply chain risk and the factors affecting that risk, none that we are aware of apply the methods to LVHV industries [11, 12, 13, 14, 15, 16]. In addition, no published works found as part of this research model supply chain reliability in terms of the metrics proposed in the SCOR[®] model.

Mixed integer programming is a common optimization method. However, when applied to supply chain risk management, many of the proposed models use expected cost or profit in the objective function [17]. Some authors propose to minimize cost in relation to site location, disaster preparedness, transportation network design, and geographic risks [18, 19, 20, 21, 22]. Instead, our research focuses on maximizing reliability across the supply chain system, which is represented as a fault tree. Similar modeling techniques have been applied to fault tree analysis and reliability optimization [23, 24]. However, not when

the underlying fault tree is constructed from a product's bill of materials and represents the supply chain system responsible for delivering that product to a firm.

CHAPTER 2

PROACTIVE COST-EFFECTIVE RISK MITIGATION IN A LOW VOLUME HIGH VALUE SUPPLY CHAIN USING FAULT TREE ANALYSIS

2.1 Introduction

In this chapter 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.

2.1.1 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 [6]. 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 [25], nuclear power plant construction [26], and shipbuilding [27]. 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 LVHV 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 chapter will focus on a proposed method to cost-effectively and proactively mitigate the risk associated with sourcing decisions in LVHV supply chains.

Airliner manufacturing is one example of a LVHV supply chain. In 2014, one report noted that since the start of manufacturing in 2007, Boeing had manufactured 228 [28] of their 787 Dreamliner aircraft at an average unit price of \$258 million [29]. As of 2011, Boeing's total expenditure on the 787 program was estimated at \$32 billion [30]. 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 [31], 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 [25].

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 [32]. 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. Do-

ing so in a quantitative manner enables businesses to make better risk-informed decisions cost-effectively.

The supply chain associated with the manufacture of LVHV 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 [1]. 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 LVHV 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 research provides a methodology to solve the problems associated with quantitatively assessing risk, selecting suppliers, and developing risk interdiction plans within a LVHV 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.

2.1.2 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 [33]. However, opportunities exist in the areas of (1) assessing risk sources, (2) defining risk and consequences, (3) identifying risk drivers, and (4) mitigating risks [6]. As a result, instruments

that model these areas associated with risk prevention are scarce as noted in several literature surveys [34, 35, 36, 22].

Researchers have analyzed supply chain risk management extensively from a qualitative point of view [37]. In their agenda for future research in the field, Juttner et al.[6] 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 [37, 8, 6, 38, 39, 33, 40] and some have focused specifically on mitigating such risks [41, 42, 43, 44, 45]. However, empirically based published work in the area remained sparse until recently and approaches have varied [46, 8]. In a review of quantitative models for managing supply chain risks, Tang [17] 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 [47] 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 [48]. 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 [49]. Other research incorporates order quantities and capacity constraints into the supplier selection decision making process [50, 51]. Methods include the analytical hierarchy process, goal programming, data envelopment, fuzzy set theory, genetic algorithms, and others [52, 53, 54, 55, 56, 57, 58, 59]. However, consideration for the impact on business objectives is lacking [60].

The area of supply chain disruption has been studied extensively. Blackhurst et al. [61] 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 [62, 63], natural disasters [64], sourcing decisions [65], demand [66, 67, 68], and others are discussed in the literature as well as strategic frameworks and supply chain design methodologies [69, 70, 71, 72, 73] by which to manage and mitigate those threats. Work by researchers such as Snyder [74] and Cui [21] present models that consider risk in facility location as a method of risk management within supply chains. Inventory buffers [75, 36, 69, 73] and product mix [76] 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 [77, 78].

Fault tree analysis was originally developed by Bell Telephone Laboratories to evaluate the launch control system of the Minuteman Missile in 1961 [79, 80]. 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 [81, 82]. 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 Merkurjev [83] 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 [80, 84, 85, 86, 87, 88, 89, 90, 91, 92] or may reference an element of the supply chain as part of the larger system being studied as an event within the fault tree [93]. Other authors [42, 33, 39, 94] 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 [95, 96, 97, 47]. 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 [94] are made to estimate failure rates and probabilities when fault tree analysis is 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 research, 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 bills of material 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 transparent. 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.

2.1.3 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 research 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 LVHV 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 associated 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.

2.2 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 [98] 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 [99]. 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.

2.2.1 Fault Tree Formulation

In a fault tree, the main failure event of interest is called the top event [100]. For the purposes of the approach described in this chapter, 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. 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 research, 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 [101]. In other words, unreliability ($F(t)$) is the probability that the system experiences at least one failure during a specified time period, which 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.

A thrust bearing is used to illustrate the concept (see Figure 2.1) and is representative of a LVHV 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, and 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).

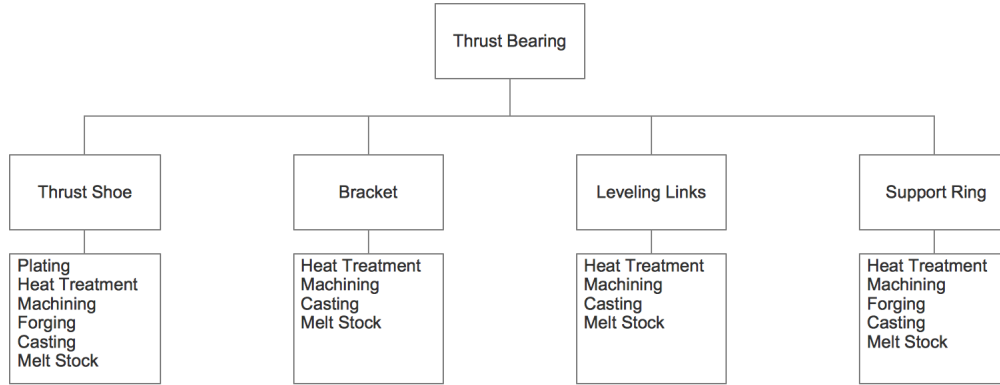


Figure 2.1: Thrust bearing bill of material.

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 2.1 summarizes the basic services used to manufacture the thrust bearing.

Table 2.1: 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 (2.1). Table 2.2 summarizes the probability that each supplier fails to deliver the respective service on-time.

$$f_{ij} = 1 - \frac{\sum_{ij} x_{ij}}{\sum_{ij} y_{ij}} \quad (2.1)$$

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

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

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

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

$i \in [1, n]$

$j \in [1, m]$

n = total number of basic services within supply chain

m = total number of suppliers within supply chain

Table 2.2: 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 [102]. 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 - *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 (2.2) and (2.3) 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 minimal cut set approach for analyzing fault trees is more appropriate [103].

$$g_k^{OR} = 1 - \prod_{i,j} (1 - f_{ij}) \quad (2.2)$$

$$g_k^{AND} = \prod_{i,j} f_{ij} \quad (2.3)$$

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 is analogous 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 2.2 illustrates the baseline case of the fault tree that describes the supply chain associated with the manufacture of a thrust bearing and Table 2.3 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.

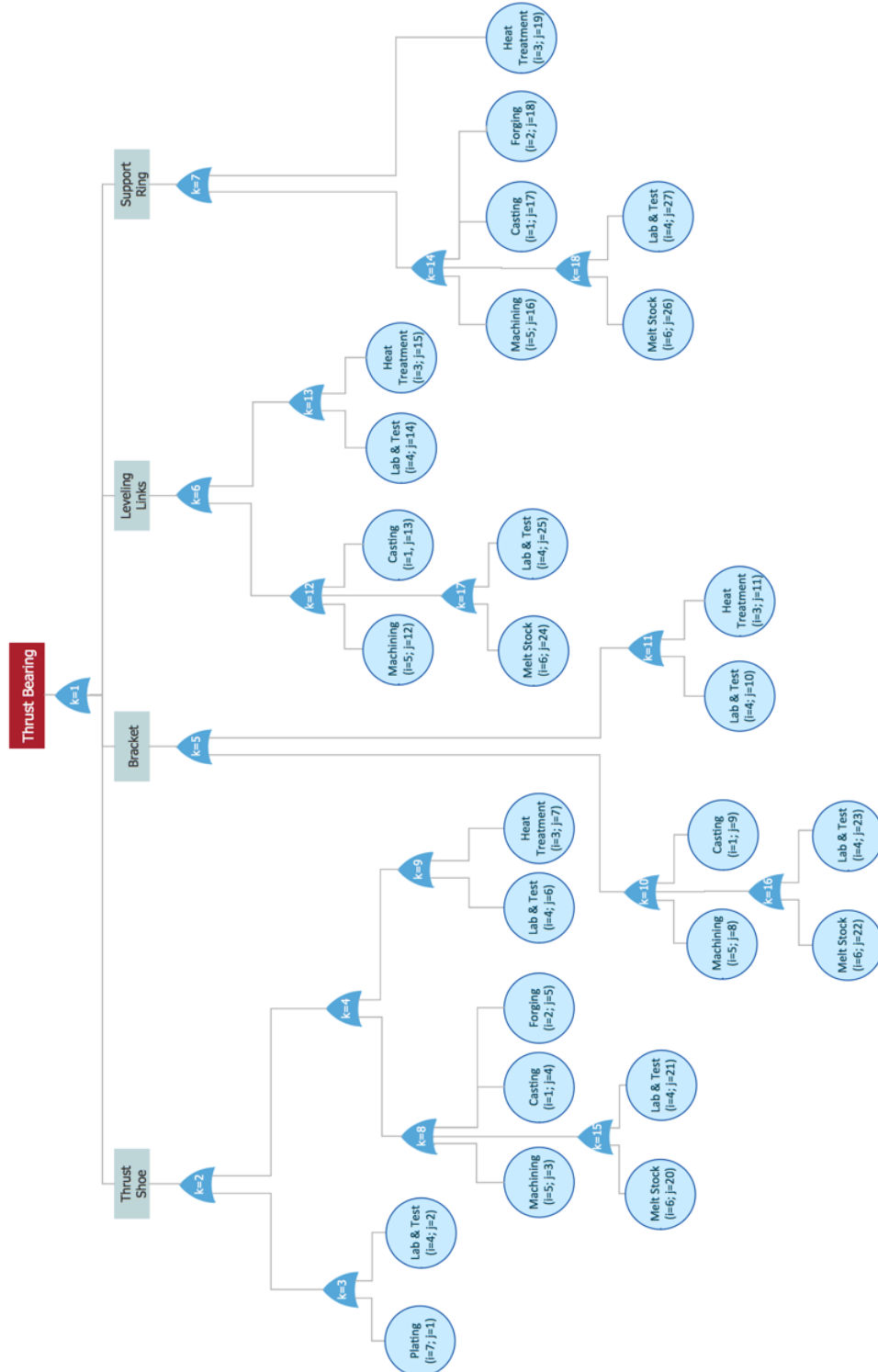


Figure 2.2: Baseline fault tree.

Table 2.3: 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 [100]. In the context of this research, 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 LVHV 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 minimal 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 [100]. 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.

2.2.2 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 (2.4), (2.5), and (2.6) describe the time to (1) improve a supplier (Equation (2.4)), (2) onboard a supplier (Equation (2.5)), and (3) provide oversight at a supplier (Equation (2.6)). 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 [104] for a LVHV industry. The models are annualized for comparison purposes and travel costs and other expenses are not included in the cost estimate. Table 2.4 summarizes the time func-

tions 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.

$$t_{ij}^{improve} = 4278u^{1.84}, \quad (2.4)$$

$$t_{ij}^{onboard} = 43e^{3.83f_{ij}}, \quad (2.5)$$

$$t_{ij}^{oversight} = 23e^{2.64f_{ij}}, \quad (2.6)$$

$$u = 1 - \frac{f_{ij,S_2}}{f_{ij,S_1}} \quad (2.7)$$

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 2.4: 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 (2.4), (2.5), and (2.6) in combination with Table 2.4, 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 2.2) from 0.1263 to 0.0947 (25% reduction) results in an improvement ratio (Equation (2.7)) of $u = 0.25$. Using Equation (2.4), the time required to reduce this particular casting supplier's unreliability by 25% is 334.3 hours and subsequently costs the firm \$34,763 using the information described in Table 2.4. If that same casting supplier ($j = 13$) was replaced by a casting supplier with an unreliability of 0.0947, the time to onboard (Equation (2.5)) the new supplier is 61.8 hours, which corresponds to a cost of \$6,427. Similarly, using Equation (2.6), 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.

2.3 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 2.2 is used as the baseline scenario. Table 2.2 includes the event data used as input to the fault tree and is updated accordingly for each scenario discussed.

2.3.1 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 (2.5), Table 2.4). Table 2.5 includes the data associated with the second casting supplier. Figure 2.3 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 2.6 contains the corresponding data. All other aspects of the fault tree architecture remain the same.

Table 2.5: Second casting source ($j = 28$) data table.

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

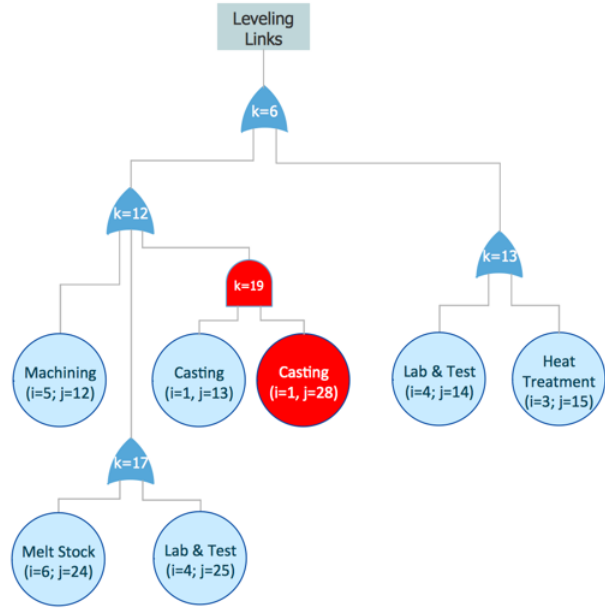


Figure 2.3: Modification to baseline fault tree architecture for Scenario 1.

Table 2.6: 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

2.3.2 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 2.2). However, the supplier's unreliability ($f_{1,13}$) is reduced by 25% (from 0.1263 to 0.0947). Table 2.8 shows the updated gate calculation results for Scenario 2. Using Equation (2.4) and the information contained in Table 2.4, 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 (2.5) and Table 2.4). 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 2.7 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 2.7: Improve (or Replace) existing casting source ($j = 13$) data table.

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

Table 2.8: 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

2.3.3 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 2.4 and Table 2.10). 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 2.9. Overall, the risk mitigating actions taken in Scenario 3 result in an approximately 6.5% reduction in system unreliability.

Table 2.9: Improved second casting source data table.

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

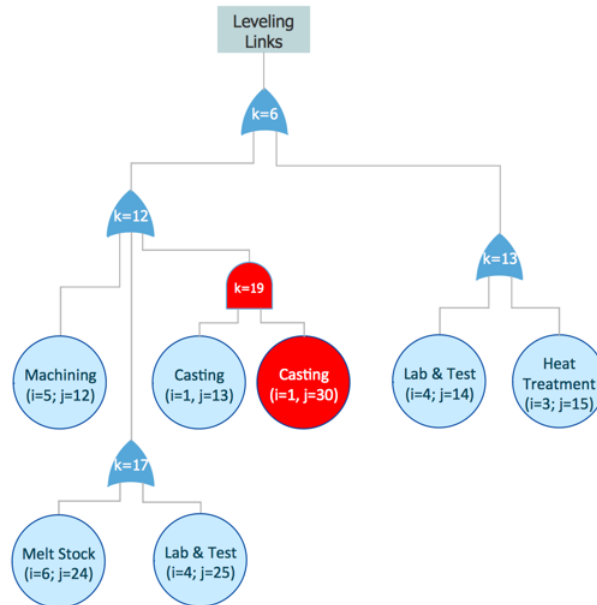


Figure 2.4: Modification to baseline fault tree architecture for Scenario 3.

Table 2.10: 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

2.3.4 Summary

Table 2.11 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 2.5 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, LVHV 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 2.11: Summary of results.

Scenario	Decision	System	Scenario	Total Mitigation	System
		Unreliability (F_S)			Mitigation Cost
0	Baseline	0.6692	\$3,339	\$3,339	–
1	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	Second Improved Supplier	0.6259	\$6,427	\$9,766	6.5%

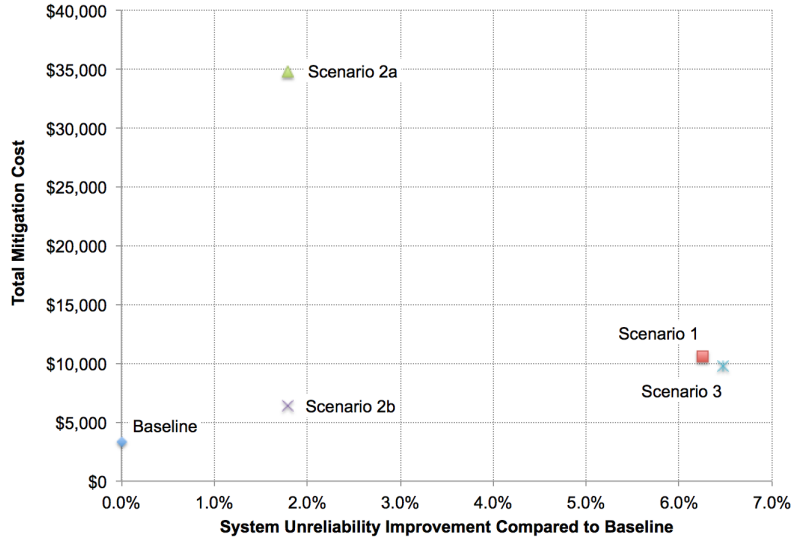


Figure 2.5: Tradeoff between risk reduction and mitigation costs for reducing risk.

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 be 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.

2.4 Conclusions and Future Work

In this chapter 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 LVHV 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 research 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 minimal cut set analysis in lieu of the simplified gate calculation approach employed 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.

CHAPTER 3
IDENTIFYING AND MITIGATING SUPPLY CHAIN RISKS USING FAULT TREE
OPTIMIZATION

3.1 Introduction

Firms that produce a low volume of high value goods with long lead times experience risk in a more significant way. According to the World Nuclear Association (www.world-nuclear.org), building a nuclear power plant costs as much as \$14 billion and takes more than 5 years to complete. Delays to complete the project can cost \$1.2 million per day. In addition, the effort is quite complex. Construction of a nuclear power plant relies on more than 5,000 individual components that are sourced from hundreds of global suppliers.

For example, the purchase order for a forging may be placed two years in advance of it being used in the manufacture of a thrust bearing used in a nuclear power plant. This lengthy lead time is necessary in order to account for raw material lead times as well as the production schedule for the forger, which may be only one of a few in the world with the requisite equipment and qualifications to make the forging. If a problem is discovered with the forging at a late stage of manufacturing or delays are experienced due to labor, equipment, or quality problems with the forger or their raw material sources, the cascading effect can be significant. Long lead times, demand for increasingly scarce capabilities,

and fewer and fewer suppliers that are qualified to meet the stringent requirements create significant risk for firms within the nuclear power plant construction supply chain. These risks are confounded due to the low volume, costly barriers to entry, and relatively infrequent demand, which decentivizes new firms from participating in the supply chain. Thus, LVHV firms like those in the nuclear industry are especially vulnerable to supply chain risks.

Supply chain risk management (SCRM), which is already an extensively studied topic, recently became a popular area of interest because supply chains are experiencing greater exposure to risk. This greater risk is the result of recent changes in how businesses are being managed. Juttner et al [6] identified the following business practices that have contributed to these increased risks: (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. Many industries, including those comprised of LVHV supply chains, have experienced an increase in supply chain risks as a result of these practices.

As a result, an opportunity exists for the development of a quantitative approach that considers all suppliers within the supply chain as a portfolio and enables supply chain professionals with the requisite information to identify risks, select suppliers, and deploy risk mitigating tactics in advance of risks being realized. Some of the current literature in supply chain risk management addresses these topics. However, not in the same manner as presented here. With the advancement of enterprise resource planning systems, data-driven decision models have the potential to be implemented in real-time, dynamically,

and with consideration for cost and resource constraints. The purpose of this research is to advance prior work by developing such data-driven models. Although all supply chains could benefit from such an approach, LVHV industries that have high risk exposure would benefit most from the proposed methods. The unique risk exposure in LVHV supply chains results from a scarce supply of capable providers, low quantities of demand, significant capital investment, and long lead times to manufacture such goods.

This research extends the work of Sherwin et al. [105] by using a fault tree representation of a LVHV supply chain system to determine how and where to best mitigate risk in the supply chain. Optimization models are developed to assist decision makers by identifying the most at-risk suppliers within the supply chain being studied with consideration for budgetary constraints. The approach is flexible and based on the perspective of the decision maker. For example, a firm constructing a nuclear power plant may utilize the proposed methodology just as easily as a manufacturer that produces one of the components that will be installed in the nuclear power plant. More specifically, the firm constructing the nuclear power plant may have the following items on their respective bill of materials - containment structure, control rods, generator, turbine, fuel rods, etc. Similarly, the proposed models could be used by the manufacturer of the turbine in which case items such as bearings, seals, and motors that comprise the turbine would be the basis for the construction of the fault tree. This approach enables a system view of the supply chain as well as modularity for the user to include and/or exclude portions of the supply chain during their analysis.

The primary objective of this research is to construct a model that identifies supplier-item combinations of greatest risk within a supply chain system and subsequently allocates scarce resources to mitigate those risks. In summary, our research solves this practical problem and makes the following contributions to the field of supply chain risk management:

1. This is the first study that addresses risk mitigation in LVHV supply chains. LVHV supply chains are different than high volume supply chains in that LVHV supply chains are more susceptible to risk given that firms with the requisite capabilities and qualifications are often more scarce due to significant administrative and capital barriers to entry. We utilize fault tree analysis to represent a supply chain as a portfolio of suppliers and services. The top-level product's bill of materials serves as a basis for the fault tree. Subsequently, we derive an optimization model that minimizes portfolio risk and recommends actions external to the firm to mitigate risks with consideration for a firm's budgetary constraints.
2. Demonstrates the practical application of the above contribution in the form of a case study to a real and current problem in order to demonstrate the practical application of the approach in mitigating supply chain risk.

In the next section, we present a literature review of related work followed by a formulation of the models. We then apply the models to solve a problem that faces supply chain professionals within the nuclear power industry. The chapter concludes with a discussion of the results.

3.2 Literature Review

Since the early part of the 21st century there has been a significant increase in the number of published papers in the area of supply chain risk modeling [10]. The SCRM literature contains conceptual, quantitative, and qualitative methodologies applied to four primary elements of research: identification, assessment, mitigation, and responsiveness

[46]. In this section, we present a review of current literature in those areas of research most relevant to this research.

With respect to risk identification and mitigation, Colicchia and Strozzi [106] identified “Complexity & Uncertainty” and “Practices & Tools for Supply Chain Risk Management” as two of the main themes within SCRM research. More specifically, the authors point out that these areas of research are moving from operational risk management to disruption risk management. Although several papers have been published in these areas within the past few years, the research has primarily focused on strategic decision making [94], site location selection [107, 74], inventory stocking levels [69, 65], and transportation decision models [108] to mitigate risk. Other research has focused on response strategies once a risk has been realized [109, 110].

Both qualitative and quantitative approaches are proposed in the literature in the areas of supply chain disruption, reliability, and risk management. Quantitative approaches to SCRM [111, 112, 94, 33, 113] focus on categorizing supply chain disruptions and analyzing the major causes of risk in the supply chain. Although useful, qualitative approaches can be biased by personal opinion, limited by personal experience, and may be more susceptible to error than quantitative approaches.

In a robust review of operations research and management science models that address supply chain disruptions, Snyder et al. [114] placed disruptions in the context of other forms of supply uncertainty (yield uncertainty, capacity uncertainty, lead-time uncertainty, and input cost uncertainty) and discussed different models for these disruptions. The authors evaluated the methods across six categories - (1) strategic decisions, (2) evaluating

supply disruptions, (3) sourcing decisions, (4) contracts and incentives, (5) inventory, and (6) facility location. With respect to the state-of-the-art in modeling disruptions, Snyder et al. note that most papers model disruptions in an abstract way and commonly assume that two states exist - normally functioning or disrupted.

In their tutorial on models for designing supply chains resilient to disruptions, Snyder et. al [73] classify models for reliable supply chain design into three categories - (1) design vs. fortification, (2) underlying model, and (3) risk measure. The authors note that supply chain systems can often be made substantially more reliable with only small additional investments in infrastructure and conclude that most of the existing models use some variation of a minimum-cost objective. Although minimizing cost is important, the authors suggest that reliability is important as well. The models developed throughout this research address these important points made by the authors. First, we include objective functions that seek to minimize the unreliability (maximize reliability) of the supply chain system being studied. Second, the models aim to provide decision makers with options to make investments within the supply chain to mitigate risk with consideration for budgetary constraints.

With regard to strategies for mitigating disruptions, models that incorporate inventory control, sourcing strategies, and rerouting contingencies have been proposed [69] as a means to proactively mitigate risk in a quantitative fashion. Other authors have investigated financial risk sharing within a supply chain via contracts, pricing, or competition [115, 116, 117]. Although research focused on supply chain risk management and related areas has increased in recent years, there is a need for approaches that join both ma-

ture (e.g., tactical/operational planning, demand/supply forecasting) and emergent areas (e.g., sourcing/supply uncertainty modeling, sustainability risk analysis) [111, 10]. Traditional quantitative OR/MS methodologies such as mixed integer programming [74, 21, 118, 119, 120], stochastic programming [121, 122, 123, 124, 69, 125], fuzzy optimization [126, 47, 127, 128, 129], and simulation [36, 83, 130] have been applied to solve the supply chain disruption problem quantitatively. Some quantitative approaches assess probabilities through surveys of experienced personnel [131, 126] in lieu of empirical data. Ivanov et al. [132] note that it is almost impossible to determine the probability of endemic-type risks such as fires, natural disasters, or piracy. Simchi-Levi et al. [133, 134] have developed a model to determine the impact of a disruption in the supply chain regardless of the cause or likelihood and use a risk-exposure model to assess the impact of disruptions originating in an automotive supply chain with a specific emphasis on low probability risks with high potential impact. Our approach is to use supplier and item historical data that is available from a firm's enterprise resource planning (ERP) system to assess the overall risk of a supply chain. This alleviates the biases that are inherent with interviews and surveys as well as the aggregation of the data resulting from those surveys. Further, our approach is not as heavily weighted as other approaches are on endemic risks and instead focuses on the past performance of a given supplier to deliver a particular item as an indicator of future risk. In highly regulated, LVHV (e.g., nuclear power plant construction) where supplier turnover is low and the use of single and sole sources is high, this is a practical approach.

Similar to Osadchiy et al. [135], our research develops models that analyze the impact of supply network structure on risk. More specifically, Osadchiy et al. identify three

mechanisms that can affect the correlation between sales and the state of the economy in a supply chain network: propagation of systematic risk into production decisions, aggregation of orders from multiple customers in a supply chain network, and aggregation of orders over time. The primary contribution of the research shows that systemic risk is an important phenomenon and is affected by supply chain structure. Our approach, based on the bill of materials of the product being sourced, leverages this concept by defining and calculating risk as a function of the structure of the supply chain being studied.

Reliability optimization research has been important since the 1960s with a focus on maximizing system reliability. Approaches have varied and are primarily based on the system structure and optimization method. [136]. Examples of system structures include parallel-series systems, general network systems, and *k-out-of-n* systems. Optimization methods include redundancy allocation algorithms [137], reliability-redundancy allocation heuristics, multi-objective reliability optimization [138], and optimal assignment of interchangeable components. More specific examples of reliability optimization methods include the use of genetic algorithms [139], simulated annealing [140], and tabu search [141].

Fault tree analysis was originally developed by Bell Telephone Laboratories in 1961 and has been used extensively in assessing and solving problems related to process hazards, risk, and system reliability [80]. Although fault tree analysis and reliability optimization are well developed areas, representing a supply chain system as a fault tree and basing the fault tree on the supply chain's bill of materials is a new and novel concept that has not previously been addressed in the literature. In one paper, Klimov and Merkurjev [83] propose

a quantitative approach to identify risks within a supply chain. In doing so, the authors use both reliability theory as well as simulation. However, the approach results in the probability of survival for the supply chain, but does not identify specific suppliers or individual items as risk mitigation focal points. In some articles, fault tree analysis is used as a tool for supply chain risk analysis. However, specific risks within the supply chain are represented as basic events. For example, Senol et al. [142] analyze the failures associated with ship transportation within a supply chain. Examples of intermediate events within the fault tree include structural, operational, tank cleaning, and other operational risks. In another paper, Aqlan and Lam [126] use fault tree analysis to analyze risks within a supply chain and propose sets of controllable (i.e., capacity constraints, poor planning and scheduling, technical limitations, design changes, quality issues, etc.) and uncontrollable risk factors (i.e., wars, terrorism, economic issues, etc.). However, the authors neither construct specific fault trees nor identify these risks with specific suppliers like the approach presented in our research. In other cases [94], where empirical data is not available, judgmental assessments and polling are used to estimate probabilities associated with risks when fault tree analysis is applied to risk mitigation in supply chains. This approach lends itself to decisions that are less transparent to management, based on data that is inherent with bias, and time consuming to collect. We mitigate these biases and inefficiencies by introducing an approach that is based on empirical data available via most firms' ERP systems and extends the previous work of Sherwin et al. [105] by representing a supply chain portfolio as a fault tree.

By representing the supply chain as a fault tree, the methodologies outlined in this research provide a portfolio approach to supply chain risk management and demonstrate the overall unreliability of the system. Subsequently practitioners are able to identify risks and make tactical decisions at the individual supplier and item level. In addition, we convert the fault tree structure to a binary decision diagram in order to leverage the computational advantages and improve the accuracy of the resulting reliability parameters [143, 144, 145]. A holistic approach to proactively mitigate risks while considering multiple risk factors is another important contribution of our work and has been identified as a gap in the current research [146, 114]. Our approach is developed in the pages that follow and is applied to solve a problem in nuclear power plant construction; an industry that relies heavily on LVHV supply chains.

3.3 Problem Description and Model Formulations

3.3.1 Problem description

The specific problem that we consider in this research is as follows. A supply chain manager is allocated a limited budget for reducing supply chain risk. The manager seeks to use resources as effectively as possible and in doing so determines the specific suppliers to target as the subject of mitigation activities. A supplier is mitigated by performing various actions (e.g., additional oversight is provided, the supplier is engaged in improvement activities, redundant suppliers are considered), each of which reduce the probability that the supplier is late and each of which costs resources. The manager seeks to minimize the unreliability (maximize the reliability) of the entire supply chain while staying within a prescribed mitigation budget.

We approach the problem in two ways by formulating nonlinear integer programs that are subsequently reformulated into linear integer programs with the aim of improving computational efficiency. In both models, we use the term *unreliability* as a measure of risk and define it as the probability that a supplier will not deliver their respective good(s) or service(s) on-time. First, we develop a *perfect* mitigation model that is aimed at identifying areas of the supply chain that are at-risk. The next model described, which we refer to as the *imperfect* mitigation model, extends the perfect mitigation model by identifying specific mitigating actions to take on specific suppliers to improve the overall reliability of the supply chain portfolio.

3.3.2 Model Formulations

3.3.2.1 Perfect Mitigation Model

Our modeling approach is based on a fault tree structure and starts with the bill of materials for the supply chain of the top-level item or service being procured [105]. Later, we will demonstrate this methodology using two top-level items that represent the supply chains of two firms within the nuclear industry and specifically the construction of a nuclear power plant. The items are (1) a pressurized water reactor (PWR) within the nuclear power plant and (2) a steam turbine thrust bearing (STTB) that is a component within the nuclear power plant's steam turbine. In each case the top-level item's bill of materials is constructed and converted into a fault tree. Using both AND and OR gates, we are able to represent both multi source and single/sole source situations within the supply chain. In addition, the fault tree approach enables the tiers within the supply chain to be represented. Once the

fault tree has been formulated, we develop the perfect mitigation model by representing the top event of the fault tree mathematically.

For the purposes of this research, *perfect mitigation* occurs when an activity is taken that sets the reliability of the cut set equal to 100%. In our formulation of the perfect mitigation model, we assume that failure events (and subsequently minimal cut sets) are independent. This is a practical assumption given that the factors that affect delays within a LVHV manufacturing supply chain have been shown not to have a high degree of correlation [105]. By assuming mutually independent events, we are able to apply Boolean algebraic operations and calculate the probability of occurrence that at least one mode of failure (i.e., minimal cut set) within the fault tree will occur [81]. As a result, the probability of the top event (i.e., failure) of the fault tree can be stated as $1 - \prod_{i \in I} (1 - \mathbb{U}_i)$ where $(1 - \mathbb{U}_i)$ is the probability that cut set i does not occur and I is the set of all minimal cut sets.

The objective function (Eq. (3.1)) is formulated as a nonlinear integer program based on the above assumption and using the binomial decision variable x_i that is 1 if minimal cut set $i \in I$ is mitigated and 0 otherwise. Cut sets are linked to basic events (suppliers) via the model constraints and specifically a second binomial variable y_j which is 1 if supplier $j \in J$ is mitigated and 0 otherwise and J is the set of all basic events (suppliers). J_i represents the set of suppliers that are members of cut set i . A budget value, b , is included in the formulation and represents the total mitigation budget of the firm and is compared to the cost, c_j , of mitigating supplier j . The basis for c_j and its extension c_{jk} are discussed in

a later section. Given this notation, the objective of minimizing the supply chain reliability can be represented as follows:

$$\text{Minimize} \quad 1 - \prod_{i \in I} (1 - U_i)^{x_i} \quad (3.1)$$

By converting the minimization to maximization and taking the logarithm of the objective function, the perfect mitigation model is formulated as follows:

$$\text{Maximize} \quad \sum_{i \in I} \log(1 - U_i)(1 - x_i) \quad (3.2)$$

$$\text{s.t.} \quad x_i \leq \sum_{j \in J_i} y_j \quad \forall i \in I \quad (3.3)$$

$$\sum_{j \in J} c_j y_j \leq b \quad (3.4)$$

Equation (3.3) enforces that a minimal cut set can only be mitigated if at least one of its suppliers is mitigated and (3.4) enforces a budget for supplier mitigation. As mentioned above, this model assumes that if a supplier is mitigated then it cannot fail, an impractical assumption in many cases. In even the best circumstances, it is rare that a supplier will become perfectly reliable after completing mitigation actions. As a result, the perfect mitigation model computes a best-case bound and can serve as a means for practitioners to identify the areas of highest risk within the supply chain portfolio.

3.3.2.2 Imperfect Mitigation Model

Whereas the perfect mitigation model describes perfect supplier intervention, we now introduce an *imperfect mitigation model* that selects individual suppliers to mitigate within cut sets. In this scenario, supplier intervention reduces, but does not eliminate, the chance of supplier unreliability. Examples of such intervention activities that we will explore include taking action to improve the existing supplier's reliability, replace the supplier with an improved supplier, provide additional oversight to assist the supplier, or take no mitigation action at all. All of the supplier-specific activities described are intended to have a favorable impact on the overall reliability of the supply chain system and represent activities that are applied in industry settings.

For the imperfect mitigation model we convert the fault tree that represents the supply chain system into a binary decision diagram. This approach leverages the computational advantages of the binary decision diagram structure as well as more effectively models the problem such that individual suppliers can be identified as targets for risk mitigation activities that result in an overall improvement of the supply chain system reliability.

For the purpose of this research, we apply the component connection method [147] for converting a fault tree into a binary decision diagram. The process consists of three primary steps: (1) ordering, (2) construction/connection, and (3) simplification. For basic events that are connected through AND gates, the corresponding nodes on the binary decision diagram are connected to each other through the 1 branch of the node. Alternatively, for basic events that are connected via OR gates, the nodes that represent the basic events on the binary decision diagram are connected to each other on the 0 branch of the node. Figure

3.1 illustrates the conversion of a simple fault tree into a binary decision diagram using the component connection method. In this example, the fault tree contains four basic events (A, B, C, and D), one OR gate (Gate 1), and one AND gate (Gate 2). The subsequent binary decision diagram consists of five terminal 1 node paths.

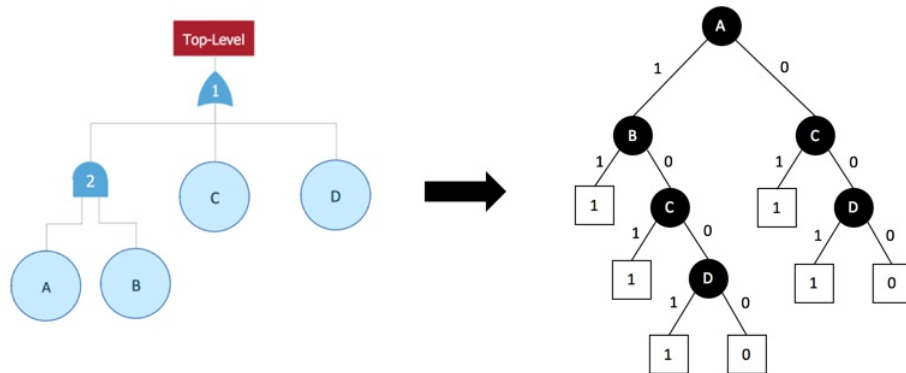


Figure 3.1: Example of converting a fault tree to a binary decision diagram.

The resulting binary decision diagram consists of nodes that represent basic events and have associated probabilities of success (reliability) and failure (unreliability). Success paths are connected via 0 branches and failure paths are connected via 1 branches. Paths consist of the sequence of connections between basic events and terminate at either a terminal 1 node or a terminal 0 node and represent the cut sets within the fault tree. Paths that lead to a terminal 1 node specify the basic events (suppliers) for the top event (i.e., failure) in the fault tree to occur. If redundancies within the binary decision diagram have been removed, the basic events (suppliers) contained within a path terminating in a terminal 1 node lie along the fault tree's minimal cut sets [148]. Conversely, the paths that terminate in a terminal 0 node indicate top event nonoccurrence (or success/reliability).

We define $\mathbb{P}_{j,\ell(j,\omega)}$ as the probability of supplier j in path ω with state ℓ where $\ell = 0$ if success state and $\ell = 1$ if failed state. $\ell(j,\omega)$ is the state of supplier j in path ω . Hereafter, the notation $\mathbb{P}_{j,\ell(j,\omega)}$ is simplified and equivalent to $\mathbb{P}_{j,\omega}$. Let Ω be the set of all terminal 1 node paths. Using the binary decision diagram approach, for a given terminal 1 path ω we can multiply the probabilities of all suppliers contained within that path (J_ω) to obtain the probability of that path. Subsequently we can take the summation across all terminal 1 paths to compute the top event (system) unreliability. For the example presented in Figure 3.1, the resulting top event unreliability can be computed as $\sum_{\omega \in \Omega} \prod_{j \in J_\omega} \mathbb{P}_{j,\omega}$ where $\Omega = \{1, 2, 3, 4, 5\}$, $J_1 = \{A, B\}$, $J_2 = \{A, B, C\}$, $J_3 = \{A, B, C, D\}$, $J_4 = \{A, C\}$, $J_5 = \{A, D\}$, and the probability of supplier j in path ω is a value dependent upon one of two states, $\ell = \{0, 1\}$.

The imperfect mitigation model (see Eq. (3.5)) is developed similarly and based on the binary decision diagram that has been converted from the fault tree that represents the supply chain structure being analyzed. The objective function is formulated as a nonlinear integer program, and seeks to minimize the overall unreliability of the supply chain system. We leverage the straightforward reliability computations of the binary decision diagram and introduce an index k to represent the mitigation activity performed on a supplier. More specifically, $\mathbb{P}_{j,\omega,k}$ is the probability of supplier j along path ω given mitigation activity k was performed on j . A binary decision variable y_{jk} is introduced and represents whether or not supplier j is mitigated using action k . The selection of mitigation activity k reduces the probability, but does not necessarily reduce the probability to 0 and in one case defined later, results in no change to the probability. Subsequently, taking the summation across

all terminal 1 paths ($\omega \in \Omega$) within the binary decision diagram results in the top event unreliability. The objective function, $\sum_{\omega \in \Omega} \prod_{j \in J_\omega} \prod_{k \in K} \mathbb{P}_{j,\omega,k}^{y_{jk}}$, represents the summation of the product of the probability of the path sets within the binary decision diagram being studied.

Two constraints are incorporated into the model (see Eq. (3.6)-(3.7)). The first is a budgetary constraint (b). The second constraint assures that, if selected, a supplier (j) is only subject to one mitigation activity (k).

In the imperfect mitigation model formulation, we extend the cost function values (c_{jk}) used in Equation (3.6) specific to the mitigation activity chosen. By taking this approach, we are able to choose the optimal portfolio of mitigation activities to take with individual suppliers that minimizes the unreliability of the supply chain system being studied within the budgetary constraints set by the firm. We have chosen four potential mitigation activities that are currently used within the nuclear industry to illustrate the concept in this research. The activities are as follows: (1) improve the existing supplier ($k = 1$), (2) replace the existing supplier with an improved supplier ($k = 2$), (3) increase oversight at the supplier ($k = 3$), and (4) do not take any mitigation action ($k = 4$). This is an advantage of the approach described here in that it allows for additional activities as well as the associated cost functions to be customized to the industry and supply chain portfolio being analyzed. Thus, the model formulation is as follows.

$$\text{Maximize} \quad \sum_{\omega \in \Omega} \prod_{j \in J_\omega} \prod_{k \in K} \mathbb{P}_{j,\omega,k}^{y_{jk}} \quad (3.5)$$

$$\text{s.t.} \quad \sum_{j \in J} c_{jk} y_{jk} \leq b \quad (3.6)$$

$$\sum_{k \in K} y_{jk} = 1 \quad (3.7)$$

Next, we present a linearized reformulation of the imperfect mitigation model. In doing so we introduce the variable w_{rk}^ω , which we will refer to as the partial probability associated with each path (ω) where k is the mitigation activity select and r is the order of the supplier within the given path. The variable $w_{rk}^\omega = \mathbb{P}_{j(1,\omega),\ell(1,\omega),k(1,\omega)} \mathbb{P}_{j(2,\omega),\ell(2,\omega),k(2,\omega)} \dots \mathbb{P}_{j(r,\omega),\ell(r,\omega),k(r,\omega)}$ represents the probability that the first r suppliers within path ω realize the respective state (ℓ) assigned to them within the path given that k is the mitigation level for r^{th} supplier j in path ω . Equations (3.8) - (3.13) outline the linearized reformulation of the imperfect mitigation model. The objective function (3.8) is the summation of the partial probability for the last supplier in the path across all paths in the BDD and all mitigation activities. The first constraint (3.9) is the probability of the first member ($r = 1$) of each path and incorporates the decision variable, $y_{j(1,\omega),k}$. For each path, the second constraint (3.10) identifies the r th partial probability (w_{rk}^ω for some value of k) as the product of the $(r - 1)$ th partial probability ($w_{r-1,k}^\omega$ for some value of k) and the probability that the r th supplier is in state ℓ on the path ($\mathbb{P}_{j(r,\omega),\ell(r,\omega),k(r,\omega)}$ for some value of k); this “chain” starts with the second supplier in the path and continues to the last supplier. In this way, the partial probability of the last supplier in path ω ($w_{|J_\omega|,k}^\omega$) is the product of the state probabilities of all of the

suppliers in the path. The third constraint (3.11) assures that for each path ω the partial probability w_{rk}^ω is always non-negative and is positive only for the value of r and k such that $y_{j(r,\omega),k} = 1$. The fourth constraint (3.12) serves as the budgetary constraint and the fifth constraint (3.13) assures that only one mitigation activity (k) is selected for each supplier (j).

$$\text{Maximize} \quad \sum_{\omega \in \Omega} \sum_{k \in K} w_{|J_\omega|,k}^\omega \quad (3.8)$$

$$\text{s.t.} \quad w_{1k}^\omega = \mathbb{P}_{j(1,\omega),\ell(1,\omega),k(1,\omega)} y_{j(1,\omega),k} \quad \forall k \in K; \omega \in \Omega \quad (3.9)$$

$$\sum_{k \in K} w_{r-1,k}^\omega = \sum_{k \in K} \frac{1}{\mathbb{P}_{j(r,\omega),\ell(r,\omega),k(r,\omega)}} w_{rk}^\omega \quad (3.10)$$

$$\forall \omega \in \Omega; \forall j \in J; r = 2, \dots, |J_\omega|$$

$$w_{rk}^\omega \leq y_{j(r,\omega),k} \quad \forall j \in J; k \in K; \omega \in \Omega \quad (3.11)$$

$$\sum_{j \in J} c_{jk} y_{jk} \leq b \quad (3.12)$$

$$\sum_{k \in K} y_{jk} = 1 \quad (3.13)$$

The rationale for this linearized model is as follows. Let k_j^* be the mitigation level selected for supplier j in the optimal solution (i.e., the value of k for which $y_{jk} = 1$). Then the recursive equations are as follows where Equation (3.14) represents the partial probability of the first ($r = 1$) supplier in each path (ω) and Equation (3.15) represents the partial probabilities of each path (ω) inclusive of all suppliers ($|J_\omega|$) within the path beginning with the second ($r = 2$) supplier in the path.

$$w_{1k^*(1)}^\omega = \mathbb{P}_{j(1,\omega),\ell(1,\omega),k^*(1,\omega)} \quad \omega \in \Omega \quad (3.14)$$

$$\mathbb{P}_{j(r,\omega),\ell(r,\omega),k^*(r,\omega)} w_{r-1,k^*(r-1)}^\omega = w_{rk^*(r)}^\omega \quad r = 2, \dots, |J_\omega|; \omega \in \Omega \quad (3.15)$$

As an example, suppose that we mitigate supplier $r-1$ by choosing $k=2$ and supplier r by choosing mitigation activity $k=1$. It follows that:

$$w_{r-1,1}^\omega + w_{r-1,2}^\omega = \frac{1}{\mathbb{P}_{j(r,\omega),\ell(r,\omega),1}} w_{r1}^\omega + \frac{1}{\mathbb{P}_{j(r,\omega),\ell(r,\omega),2}} w_{r2}^\omega \quad r = 2, \dots, |J_\omega|; \omega \in \Omega \quad (3.16)$$

Because $w_{r-1,1}^\omega = 0$ and $w_{r2}^\omega = 0$,

$$w_{r-1,2}^\omega = \frac{1}{\mathbb{P}_{j(r,\omega),\ell(r,\omega),1}} w_{r1}^\omega \quad r = 2, \dots, |J_\omega|; \omega \in \Omega \quad (3.17)$$

Rearranging Equation (3.17) yields the recursive equation in the format shown in Equation (3.15):

$$\mathbb{P}_{j(r,\omega),\ell(r,\omega),1} w_{r-1,2}^\omega = w_{r1}^\omega \quad r = 2, \dots, |J_\omega|; \omega \in \Omega \quad (3.18)$$

3.4 Motivating Example: Nuclear Power Plant Supply Chain

In order to demonstrate the application of our approach to supply chain risk mitigation, we illustrate the model with an example from the nuclear power industry. According to the World Nuclear Association (www.oecd-nea.org) [3], the total value of nuclear power plant construction globally between 2014 and 2030 is estimated at \$1.23 trillion and will rely on approximately \$575 billion in international procurements. According to the same report, 295 new nuclear power plants were either under construction or planned as of March 11, 2014. With continued emphasis on green energy as a means to stabilize CO_2 emissions worldwide, nuclear energy is viewed as a clean energy source that continues to be sought after by many countries.

Aside from the severity of adverse events that may result from nuclear energy, several factors exist that make nuclear energy a cost prohibitive solution. A primary factor is the requirements and standards required to enter the nuclear supply chain. As a result, many suppliers are not interested in entering the supply chain. In turn, companies responsible for constructing and maintaining nuclear power plants are faced with a limited supply base to produce critical, large, and expensive items. The quality and reliability of these items are essential to the safe operation of the nuclear power plant. Furthermore, delays in the delivery of these products to the construction site can result in losses estimated at \$1.2 million per day [149]. In the summer of 2017, construction at the Virgil C. Summer Nuclear Generating Station near Jenkinsville, SC was abandoned due to a number of factors, including the deterioration of a “robust supply chain” within the industry over the past 30 years [150].

In 2014, the industry identified two primary challenges for nuclear power to remain competitive [3]: (1) ensuring that the economics of nuclear power are competitive with other generating sources and (2) reliable international supply chains are developed that are capable of delivering high quality products. The research presented here addresses the latter, which is directly related to the overall competitiveness of nuclear power generation.

In the sections that follow, the models presented above are applied at two levels within the same supply chain. The first level analyzes the basic supply chain used in nuclear power plant construction using the proposed methods. The second level supply chain is based on the perspective of a supplier to the firm constructing the nuclear power plant and consists of a turbine, which is a key component used within the nuclear power plant. This approach demonstrates the robustness of the application of our methodology in that it applies equally well to firms at various levels of the same supply chain.

3.4.1 Supply chain definition

We have chosen the construction of a nuclear power plant and the manufacture of one of the components used in the manufacture of one of the primary items within the power plant to demonstrate the methods outlined in this research. More specifically, we have chosen a pressurized water reactor as the basis for the bill of materials of the nuclear power plant because several pressurized water reactor power plants are being constructed worldwide. Further, our focus is on the primary items sourced for the plant. We exclude building materials and other items in order to simplify the application. Figure 3.2 shows a schematic of a pressurized water reactor and its primary items [151]. We will include

the following items in the bill of materials used in our analysis in the pages that follow: containment structure, pressurizer, steam generator, control rods, reactor vessel, turbine, generator, and condenser.

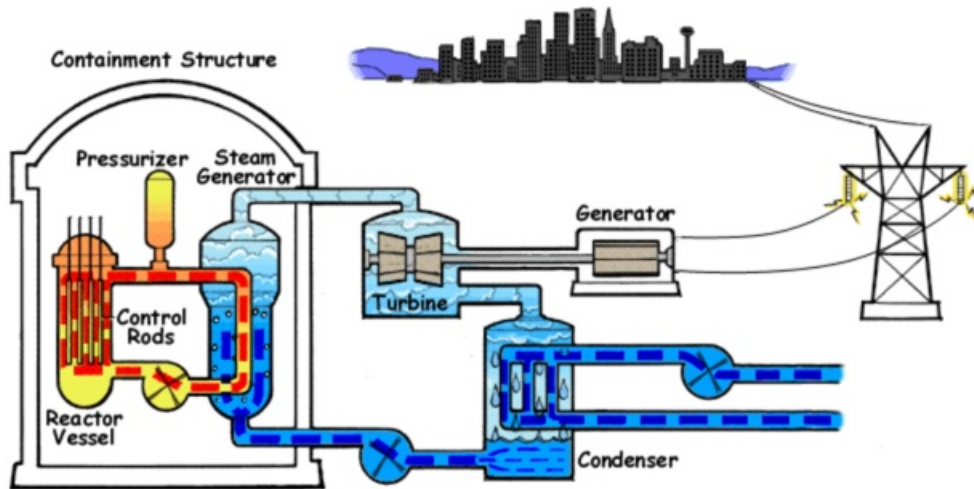


Figure 3.2: Schematic of a pressurized water reactor nuclear power plant.

One of the primary items in the pressurized water reactor is the steam turbine. Within the reactor vessel, the core creates heat. The heat is then transferred via the primary coolant loop to the steam generator where water is vaporized and produces steam. The steam is directed to the main turbine, causing it to turn the turbine generator, which results in electrical power production. [152] Steam turbine designs vary. However, the primary components of a steam turbine include the casing, valves, a rotor containing blades, diaphragms, nozzles, and a host of other auxiliary equipment that comprise the turbine system. Examples of auxiliary equipment include thrust bearings, journal bearings, couplings, and lubricating systems. For the purposes of this study, we will examine a steam turbine thrust bearing.

Figure 3.3 outlines the flow of the bills of material for the pressurized water reactor, steam turbine, and thrust bearing that will be used in the computational studies that follow. In the section that follows, we develop the fault trees and binary decision diagrams that represent the pressurized water reactor and thrust bearing supply chains. The examples that follow demonstrate the robustness of our approach at various levels of a supply chain as well as the flexibility that the approach provides in assessing, identifying, and mitigating risks at various levels of a supply chain.

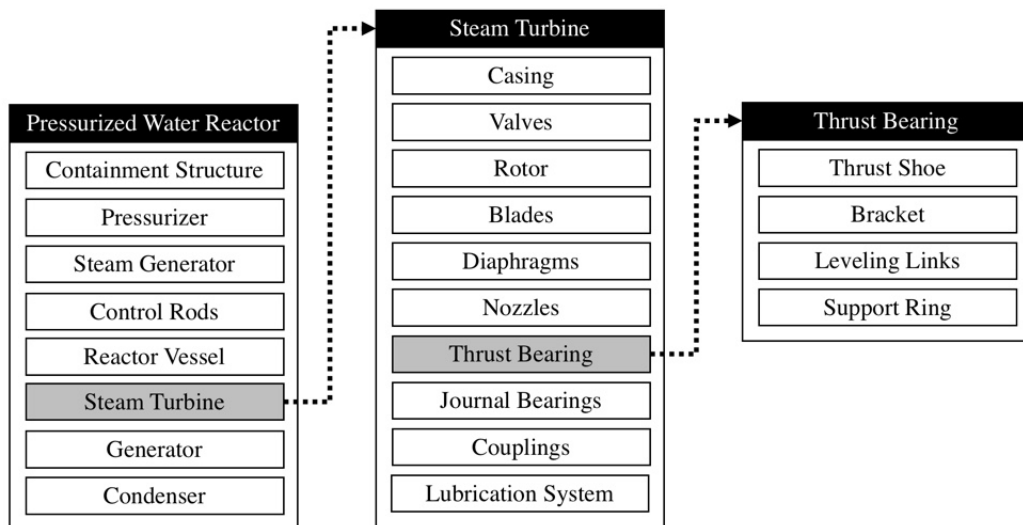


Figure 3.3: Bills of material.

3.4.2 Fault tree and binary decision diagram formulation

We introduce a fault tree and subsequently a binary decision diagram to represent each of the supply chains described above - the supply chain used to construct the pressurized water reactor and the supply chain used to manufacture a thrust bearing used in the steam

turbine, which is a primary component of the pressurized water reactor. For both the pressurized water reactor and thrust bearing supply chains, we take the perspective of the two firms responsible for outsourcing the respective goods and services. The two fault trees and two binary decision diagrams are built from the perspectives of those two firms. Basic events in the fault trees represent the primary goods and services being procured by the firm. Intermediate events are used where necessary to group lower-tier suppliers that provide more complex goods and services. The presence of dual sources (i.e., redundant suppliers) of a good and/or service are connected via AND gates. Although present within LVHV supply chains, redundancies are not common in practice and sourcing from more than two suppliers for the same good and/or service is rare. A binary decision diagram is formulated from the fault tree for the supply chain being studied using the component connection method in order to leverage the mathematical modeling advantages of binary decision diagrams [147]. Although calculating the top event probability from a fault tree is an acceptable method, doing so often requires the use of approximations and therefore, large inaccuracies may exist depending on the magnitude of the individual event probabilities and/or the size of the underlying fault tree. Even though fault trees are a preferred way to illustrate the causes of failure, the use of binary decision diagrams overcome the potential inaccuracies associated with calculating failure probabilities from a fault tree [143].

3.4.2.1 Pressurized water reactor

For the pressurized water reactor supply chain, we take the perspective of the construction firm responsible for sourcing the primary goods and services for the pressurized water

reactor. In the examples presented, we assume that multiple pressurized water reactors are being built simultaneously. As a result, dual-sourcing positions across the multiple pressurized water reactor construction sites exist for some, but not all of the goods and services being procured by the construction firm. The pressurized water reactor supply chain consists of the eight primary goods and services provided by eleven suppliers. Redundant suppliers are utilized for the control rods, the reactor vessels, and the condensers. Table 3.1 outlines the suppliers (j), their respective goods and services, and the supplier's unreliability (u_j). The unreliability numbers presented here are synthetic, but reflective of unreliabilities experienced within the nuclear industry.

Table 3.1: Pressurized water reactor supply chain data.

Supplier (j)	Good and/or Service	Supplier unreliability (u_j)
1	Containment structure	0.0031
2	Pressurizer	0.0236
3	Steam generator	0.0489
4	Control rods	0.0023
5	Control rods	0.0215
6	Reactor vessel	0.0441
7	Reactor vessel	0.0263
8	Turbine	0.0347
9	Generator	0.0088
10	Condenser	0.0288
11	Condenser	0.0411

The resulting fault tree for the pressurized water reactor can be found in Figure 3.4. Each of the goods and services provided are represented by basic events and the respective suppliers that provided them. Basic events that are inputs to the three AND gates in the fault tree include control rods, the reactor vessel, and the condenser. AND gates represent

situations where the firm constructing the pressurized water reactor has chosen dual source options. The containment structure, pressurizer, steam generator, turbine, and generator are being provided by single sources of supply in this example and the basic events that represent them are connected via OR gates in the fault tree.

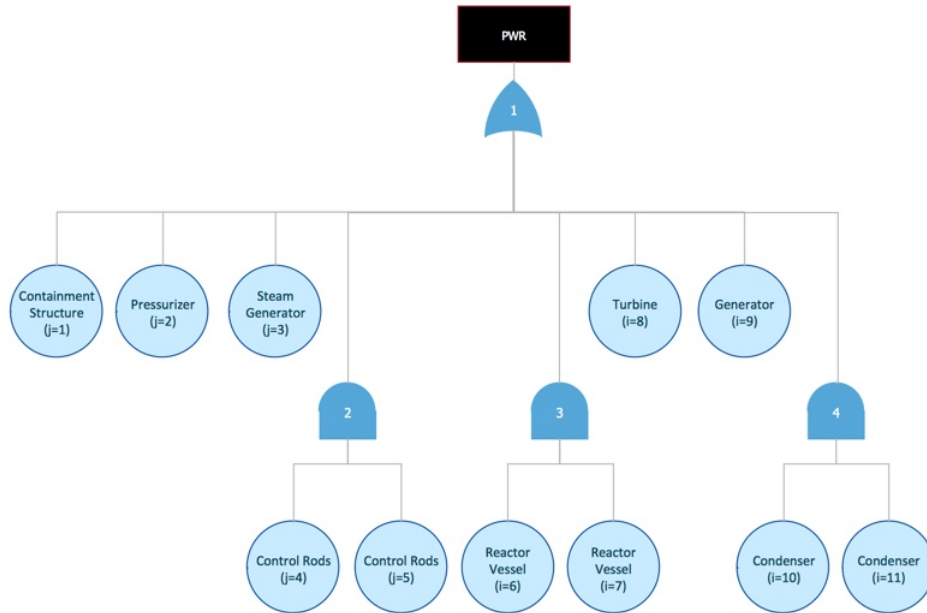


Figure 3.4: Pressurized water reactor fault tree.

A total of eight cut sets ($i = 1, \dots, 8$) result from the pressurized water reactor fault tree. Each cut set is a minimal cut set, which represents an event or series of events whose occurrence will result in the realization of the top event of the fault tree [102]. Specific to the application being discussed, the failure of the individual suppliers or the joint combination of the suppliers within a cut set to provide their respective good and service would result in the failure of the pressurized water reactor reactor being constructed on time. By assuming independence of failures between suppliers, we can apply the rules of Boolean algebra

and multiply the unreliabilities of the suppliers represented by the basic events within each cut set, which results in the unreliability of each cut set (\mathbb{U}_i). By applying the rare event approximation ($u_j < 0.1$) [102] and given that the top event unreliability is the union of the minimal cut sets, we can sum the individual minimal cut set unreliabilities to obtain the unreliability of the top event in the fault tree, $\mathcal{U}_S^{REA} = \sum \mathbb{U}_i$, where \mathcal{U}_S is the unreliability of the system being studied and *REA* denotes that \mathcal{U}_S was calculated using the rare event approximation. Likewise, the reliability of the system, \mathcal{R}_S , is equivalent to $1 - \mathcal{U}_S$. As a result, we are able to obtain the unreliability of constructing the pressurized water reactor on-time. In the case of the data presented in Table 3.1 this results in a pressurized water reactor unreliability of $\mathcal{U}_{PWR}^{REA} = 0.1215$. Table 3.2 includes the minimal cut sets and resulting unreliabilities for the pressurized water reactor fault tree. The \bullet indicates an AND gate and $+$ (not shown in the reduced form illustrated in Table 3.2) indicates an OR gate. To calculate cut set unreliability, we use Boolean algebra where the unreliabilities of events (suppliers) within the same minimal cut sets connected by AND gates are multiplied by one another and those connected by OR gates are added to one another.

Next, we construct a binary decision diagram using the component connection method. The binary decision diagram structure is used as input to the imperfect mitigation models as described above. Using the binary decision diagram provides a mathematically and computationally efficient means to identify specific basic events (suppliers) within the fault tree structure and update the overall system unreliability/reliability. Figure 3.5 is a graphical representation of the binary decision diagram based on the fault tree shown in Figure 3.4 where nodes represent suppliers.

Table 3.2: Pressurized water reactor fault tree minimal cut set data.

Minimal Cut Set		Cut Set
(<i>i</i>)	Suppliers (<i>j</i>)	Unreliability (U_i)
1	1	0.0031
2	2	0.0236
3	3	0.0489
4	4 • 5	0.0000
5	6 • 7	0.0012
6	8	0.0347
7	9	0.0088
8	10 • 11	0.0012
$\sum U_i =$		0.1215

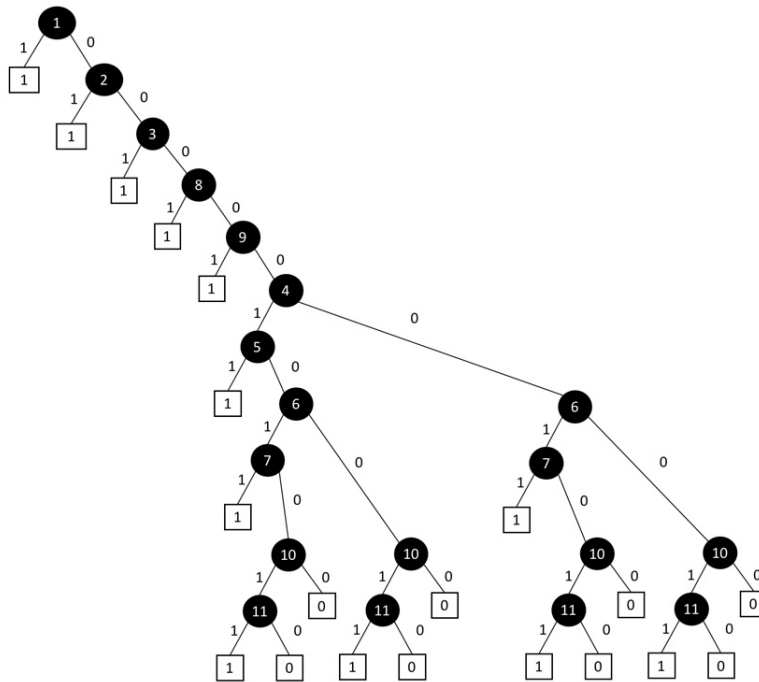


Figure 3.5: Binary decision diagram for pressurized water reactor fault tree.

3.4.2.2 Steam turbine thrust bearings

Steam turbine thrust bearings are used as a primary component in the steam turbine ($j = 8$ in the pressurized water reactor fault tree). In constructing the fault tree for the thrust bearing, we take the perspective of the firm who is the supplier to the steam turbine manufacturer. In our example, the thrust bearing manufacturer's supply chain consists of 44 suppliers (see Table 3.3 for individual supplier unreliabilities) and the resulting fault tree consists of 31 gates, which is shown in Figure 3.6.

Figures 3.6 - 3.11 illustrate the supply chains as fault trees for the items used in the manufacture of the thrust bearing. These items include the thrust shoe, bracket, leveling links, and support ring. Thrust shoes are sourced from two separate suppliers. The use of an AND gate (Gate No. 2) describes this situation within the fault tree. All other top-level items (bracket, leveling links, support ring) are procured from single or sole sources. This situation is represented by an OR gate (Gate No. 1) in the top-level fault tree (Figure 3.6). Likewise, within the lower-level fault trees (Figures 3.7-3.11), the use of AND gates and OR gates are used to describe redundant and single/sole source positions respectively.

Table 3.3: Steam turbine thrust bearing supply chain data.

Supplier (j)	Good and/or Service	Unreliability (u_j)	Supplier (j)	Good and/or Service	Unreliability (u_j)
1	Plating	0.0195	23	Lab & Test	0.0199
2	Lab & Test	0.0424	24	Melt Stock	0.0178
3	Machining	0.0379	25	Lab & Test	0.0322
4	Machining	0.0419	26	Heat Treatment	0.0492
5	Casting	0.0203	27	Heat Treatment	0.0157
6	Forging	0.0450	28	Machining	0.0422
7	Lab & Test	0.0323	29	Casting	0.0065
8	Heat Treatment	0.0081	30	Casting	0.0062
9	Melt Stock	0.0092	31	Lab & Test	0.0276
10	Lab & Test	0.0433	32	Heat Treatment	0.0097
11	Plating	0.0459	33	Heat Treatment	0.0129
12	Lab & Test	0.0316	34	Melt Stock	0.0147
13	Machining	0.0009	35	Lab & Test	0.0190
14	Casting	0.0472	36	Machining	0.0343
15	Casting	0.0062	37	Machining	0.0328
16	Lab & Test	0.0454	38	Casting	0.0049
17	Heat Treatment	0.0332	39	Forging	0.0107
18	Melt Stock	0.0016	40	Forging	0.0010
19	Lab & Test	0.0475	41	Heat Treatment	0.0425
20	Forging	0.0362	42	Heat Treatment	0.0358
21	Machining	0.0189	43	Melt Stock	0.0484
22	Casting	0.0114	44	Lab & Test	0.0095

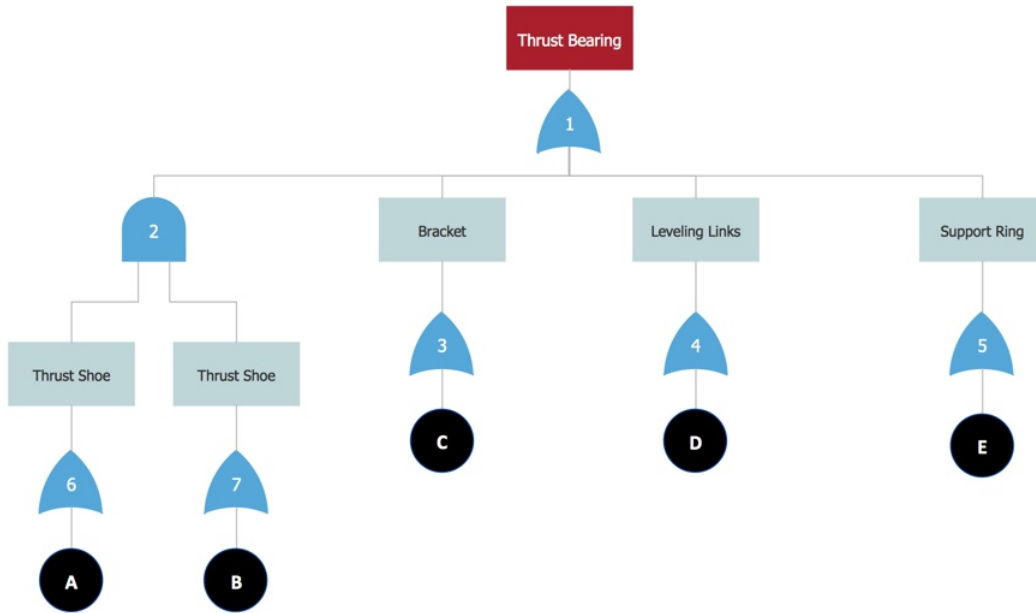


Figure 3.6: Steam turbine thrust bearing manufacturer top-level fault tree.

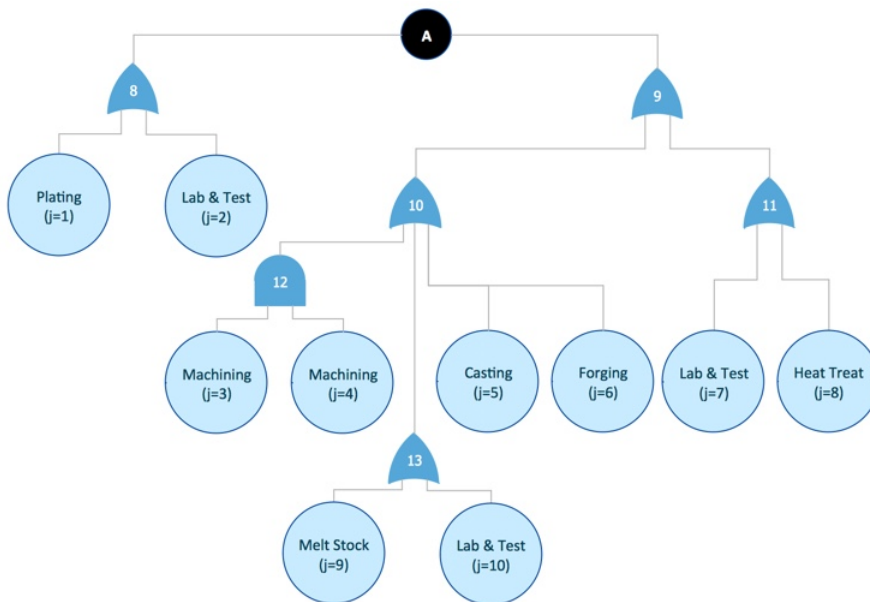


Figure 3.7: Thrust shoe supply chain (Source A).

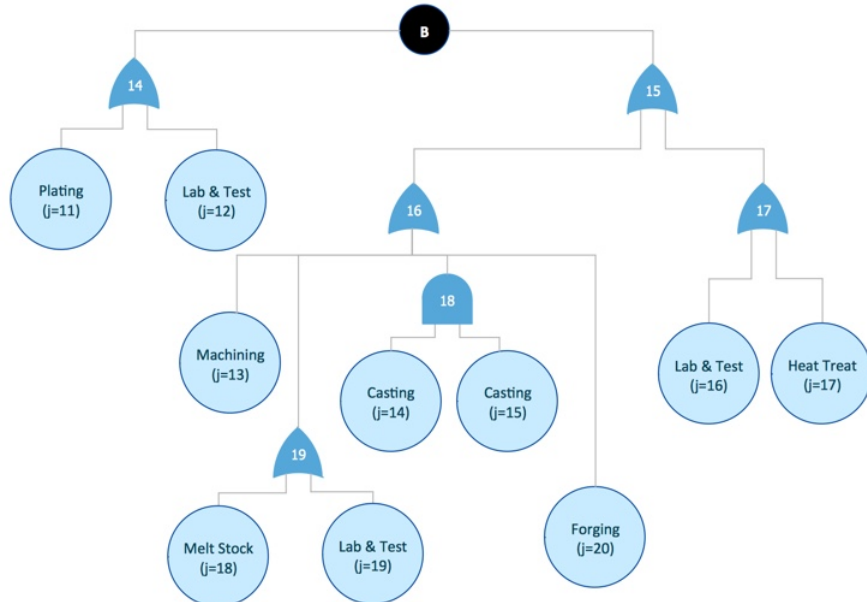


Figure 3.8: Thrust shoe supply chain (Source B).

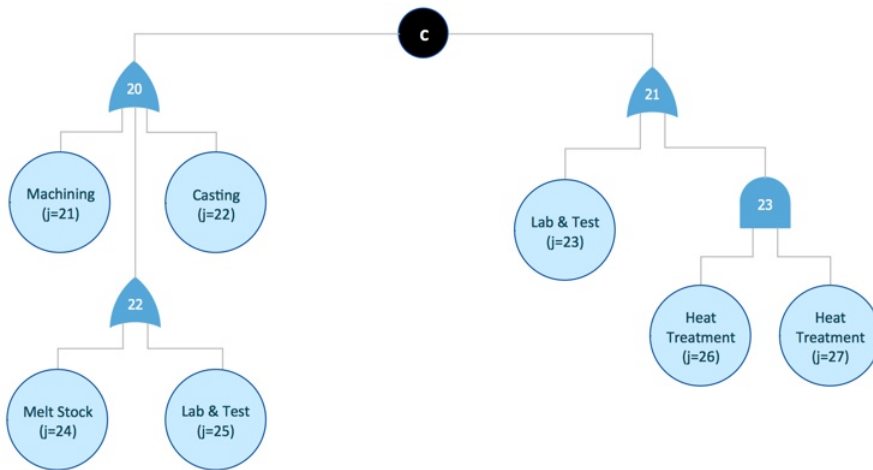


Figure 3.9: Bracket supply chain (Source C).

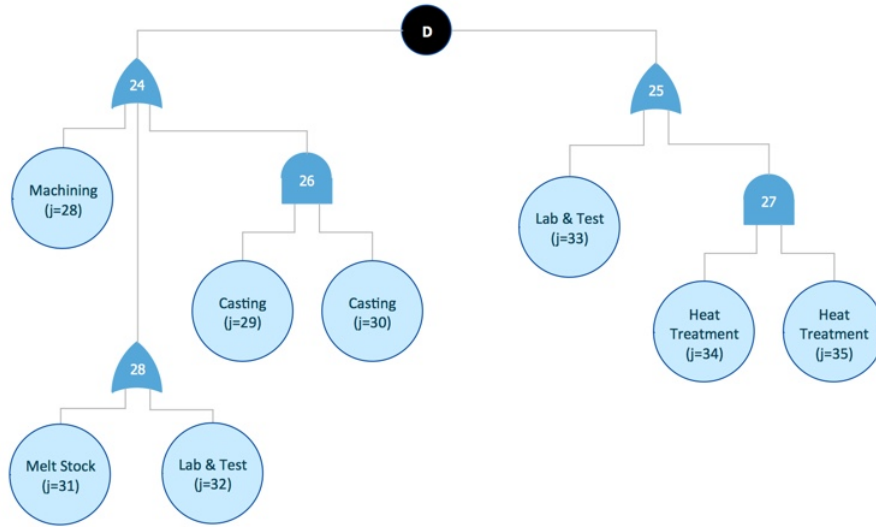


Figure 3.10: Leveling link supply chain (Source D).

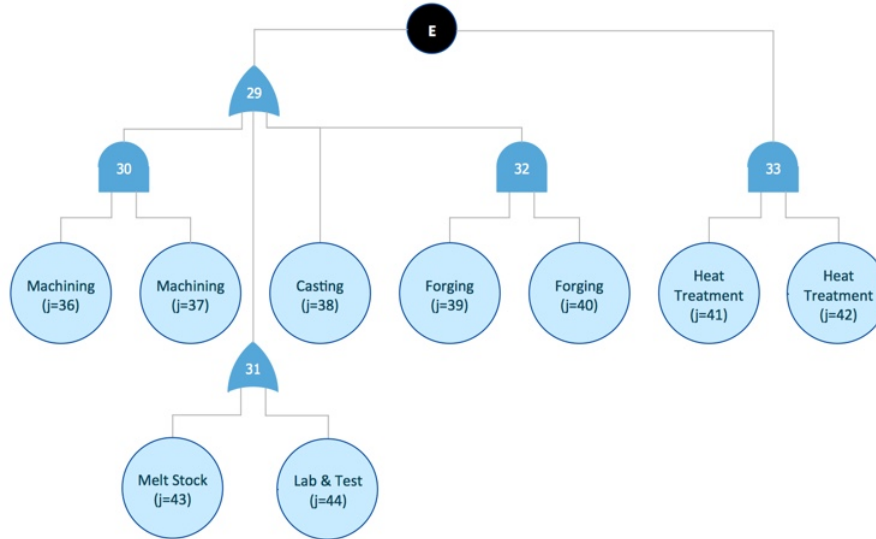


Figure 3.11: Support ring supply chain (Source E).

A total of 99 minimal cut sets are contained within the thrust bearing fault tree, which is comprised of 44 suppliers representing the supply chain used to manufacture the thrust bearing. We again apply the rare event approximation and apply the rules of Boolean algebra. The resulting steam turbine thrust bearing supply chain system unreliability is $\mathcal{U}_{STTB}^{REA} = 0.3128$. In other words, the steam turbine thrust bearing supply chain has a 31.28% probability of failure. This translates to a 31.28% probability of not being completed on-time as the result of delivery failures within the supply chain. Table 3.4 summarizes the unreliability data of the steam turbine thrust bearing supply chain fault tree minimal cut sets.

Table 3.4: Steam turbine thrust bearing fault tree minimal cut set data.

Cut Set			Cut Set			Cut Set		
Minimal	Suppliers	Unreliability	Minimal	Suppliers	Unreliability	Minimal	Suppliers	Unreliability
Cut Set (<i>i</i>)	(<i>j</i>)	(U_i)	Cut Set (<i>i</i>)	(<i>j</i>)	(U_i)	Cut Set (<i>i</i>)	(<i>j</i>)	(U_i)
1	1•11	0.00089505	34	9•20	0.00033304	67	7•18	0.00005168
2	1•12	0.00061620	35	9•16	0.00041768	68	7•19	0.00153425
3	1•13	0.00001755	36	9•17	0.00030544	69	7•14•15	0.00000945
4	1•18	0.00003120	37	10•11	0.00198747	70	7•20	0.00116926
5	1•19	0.00092625	38	10•12	0.00136828	71	7•16	0.00146642
6	1•14•15	0.00000571	39	10•13	0.00003897	72	7•17	0.00107236
7	1•20	0.00070590	40	10•18	0.00006928	73	8•11	0.00037179
8	1•16	0.00088530	41	10•19	0.00205675	74	8•12	0.00025596
9	1•17	0.00064740	42	10•14•15	0.00001267	75	8•13	0.00000729
10	2•11	0.00194616	43	10•20	0.00156746	76	8•18	0.00001296
11	2•12	0.00133984	44	10•16	0.00196582	77	8•19	0.00038475
12	2•13	0.00003816	45	10•17	0.00143756	78	8•14•15	0.00000237
13	2•18	0.00006784	46	5•11	0.00093177	79	8•20	0.00029322
14	2•19	0.00201400	47	5•12	0.00064148	80	8•16	0.00036774
15	2•14•15	0.00001241	48	5•13	0.00001827	81	8•17	0.00026892
16	2•20	0.00153488	49	5•18	0.00003248	82	21	0.01890000
17	2•16	0.00192496	50	5•19	0.00096425	83	24	0.01780000
18	2•17	0.00140768	51	5•14•15	0.00000594	84	25	0.03220000
19	3•4•11	0.00007289	52	5•20	0.00073486	85	22	0.01140000
20	3•4•12	0.00005018	53	5•16	0.00092162	86	23	0.01990000
21	3•4•13	0.00000143	54	5•17	0.00067396	87	26 • 27	0.00077244
22	3•4•18	0.00000254	55	6•11	0.00206550	88	28	0.04220000
23	3•4•19	0.00007543	56	6•12	0.00142200	89	31	0.02760000
24	3•4•14•15	0.00000046	57	6•13	0.00004050	90	32	0.00970000
25	3•4•20	0.00005749	58	6•18	0.00007200	91	29 • 30	0.00004030
26	3•4•16	0.00007210	59	6•19	0.00213750	92	33	0.01290000
27	3•4•17	0.00005272	60	6•14•15	0.00001317	93	34 • 35	0.00027930
28	9•11	0.00042228	61	6•20	0.00162900	94	36 • 37	0.00112504
29	9•12	0.00029072	62	6•16	0.00204300	95	43	0.04840000
30	9•13	0.00000828	63	6•17	0.00149400	96	44	0.00950000
31	9•18	0.00001472	64	7•11	0.00148257	97	38	0.00490000
32	9•19	0.00043700	65	7•12	0.00102068	98	39 • 40	0.00001070
33	9•14•15	0.00000269	66	7•13	0.00002907	99	41 • 42	0.00152150
							$\sum U_i =$	0.31292916

Figure 3.12 shows a portion of the overall binary decision diagram developed from the steam turbine thrust bearing fault tree and specifically the suppliers that comprise the thrust shoe supply chain (see Figure 3.7). After applying simplification rules [147], the steam turbine thrust bearing binary decision diagram consists of a total of 99 paths.

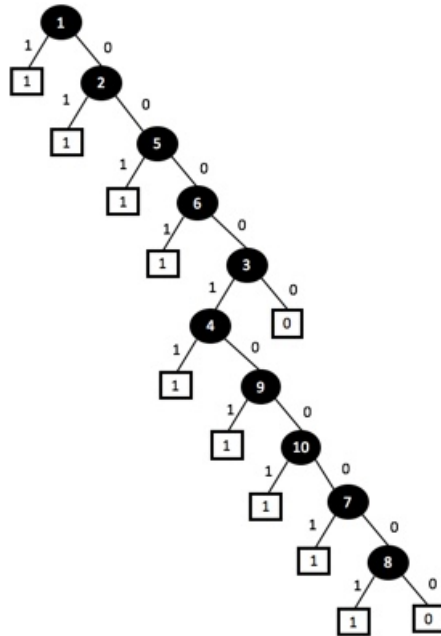


Figure 3.12: Binary decision diagram for steam turbine thrust bearing thrust shoe (see Figure 3.7).

3.4.3 Mitigation Cost

The cost of mitigating the risks of supplier j is a function of the time estimated for mitigation activity (k) and the hourly rate of personnel to complete the activity ($h = \$104$

per hour [104]). The respective costs used for the four mitigation activities available are described in Table 3.5 and were estimated empirically based on industry knowledge.

Table 3.5: Cost function values.

Mitigation Activity	k	Reliability Improvement	c_{jk}
Improve the existing supplier	1	15%	\$12,209
Replace supplier with an improved supplier	2	25%	\$27,737
Increase oversight at existing supplier	3	5%	\$10,816
No mitigation activity	4	0%	\$0

One restriction of the perfect mitigation model is that only one mitigation strategy/activity is permitted per supplier. In order to maintain consistency between the perfect mitigation model and the imperfect mitigation model for comparison purposes, we have set the mitigation cost (c_j) in the perfect mitigation model to \$12,209, which is equivalent to c_{j1} in the imperfect mitigation model even though the functions described in Table 3.5 do not apply to the perfect mitigation model.

3.5 Computational Results

For the supply chains described above, we run the respective models outlined using data representative of the suppliers of goods and services for the LVHV industry being described. The computational results are presented in a fashion relevant to the supply chain professional who, with a limited budget, will be challenged with minimizing risk across the supply chain system he/she is managing. As a result, each model is run at

\$10,000 budgetary increments up to a maximum budget of \$300,000 or an overall system reliability of 100% (0% unreliability), whichever comes first. Results are presented as a Pareto frontier and demonstrate the optimal tradeoff between the budget allocation and resulting reliability of the supply chain system being analyzed.

Both the pressurized water reactor and steam turbine thrust bearing supply chains are analyzed in the pages that follow utilizing each of the modeling approaches outlined throughout this research. In the sections that follow, we analyze the computational results of the respective models.

3.5.1 Perfect Mitigation

Here, we analyze the supply chains using the perfect mitigation model described in Equations (3.2) - (3.4). Figure 3.13 demonstrates the tradeoff between the system reliability and mitigation cost for both the pressurized water reactor and steam turbine thrust bearing supply chains independently. Prior to investing in mitigation activities, the reliability of the pressurized water reactor and steam turbine thrust bearing supply chains were $\mathcal{R}_{PWR}^{PMM} = 0.8837$ and $\mathcal{R}_{STTB}^{PMM} = 0.7285$ respectively. At successive levels of investment, the reliability of each supply chain system increases as expected. The pressurized water reactor supply chain achieves 100% reliability at a cost of \$109,881. The steam turbine thrust bearing does not achieve 100% reliability prior to exhausting the \$300,000 maximum budget. Instead, the thrust bearing supply chain sees a maximum reliability of 99.98% at a total cost of \$293,016. In both cases, the marginal improvement in system reliability decreases with increasing investment in mitigation activity. This information could prove

quite important to a practitioner responsible for allocating resources to minimizing risk within a supply chain. For example, a supply chain manager might determine that budgeting \$150,000 to increase the reliability of the thrust bearing supply chain is satisfactory given that the resulting improvement in reliability (to 95.12%) is sufficient.

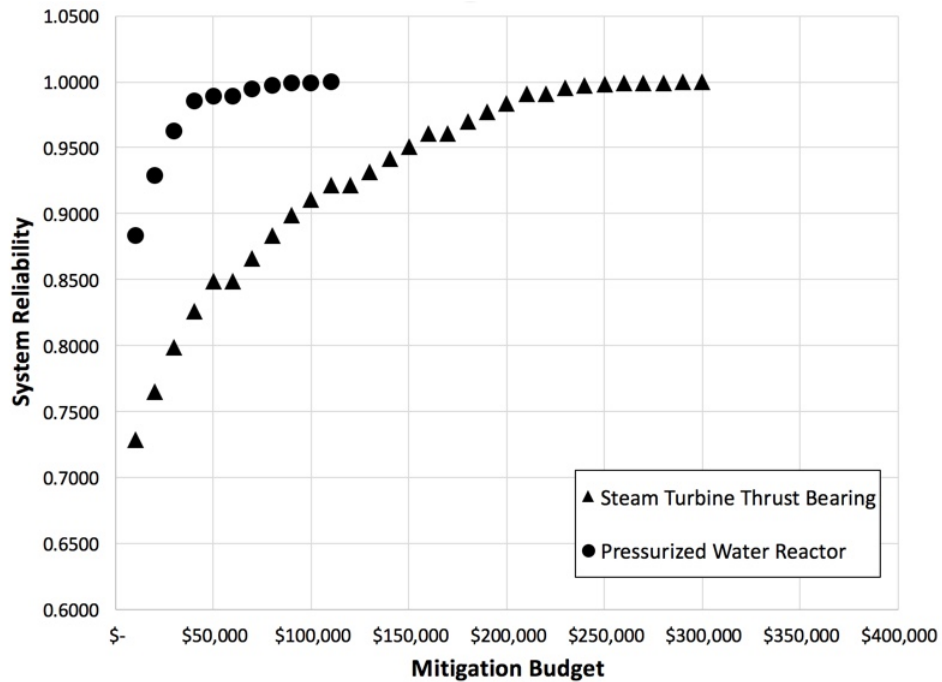


Figure 3.13: System reliability improvement as a function of mitigation budget (perfect mitigation model).

Figures 3.14 and 3.15 visually represent the optimal cut sets whose probabilities have been nullified and contains the suppliers selected to mitigate for each formulation and supply chain. In the case of the pressurized water reactor, minimal cut set 4 is not chosen. This is reasonable given the fact that the cut set is already 100% reliable without any mitigation. Minimal cut sets 6, 24, 33, 51, 78, 91, and 98 are not chosen by the model

in the thrust bearing supply chain system. Similar to minimal cut set 4 in the pressurized water reactor supply chain, the minimal cut sets not chosen in the thrust bearing supply chain have unreliability values nearing 100% ($U_i \sim 0.0000$). Thus, taking mitigating actions would provide nearly no marginal benefit to the system's overall reliability.

Budget	Minimal Cut Set							
	1	2	3	4	5	6	7	8
\$10,000								
\$20,000								
\$30,000								
\$40,000								
\$50,000								
\$60,000								
\$70,000								
\$80,000								
\$90,000								
\$100,000								
\$110,000								

Figure 3.14: Minimal cut sets mitigated in pressurized water reactor supply chain.

3.5.2 Imperfect Mitigation

Equations (3.8) - (3.13) develop the formulation of the linearized imperfect mitigation model used to analyze the pressurized water reactor and steam turbine thrust bearing supply chains. Prior to investment or taking any mitigating actions, the system reliabilities of the pressurized water reactor and steam turbine thrust bearing supply chains were $\mathcal{R}_{PWR}^{IMM} = 0.8836$ and $\mathcal{R}_{STTB}^{IMM} = 0.7982$. Figure 3.16 illustrates the tradeoff between increasing investments in mitigating activities and the improvement in supply chain reliability. At a total mitigation budget of \$300,000 neither of the supply chains had achieved 100% system reliability ($\mathcal{R}_{PWR}^{IMM} = 0.9122$, $\mathcal{R}_{STTB}^{IMM} = 0.8354$). Figure 3.17 illustrates the suppliers and mitigation activities selected as a function of increasing investment in risk mitigation activities for the pressurized water reactor supply chain. In the case of the imperfect mitigation model, risk mitigation activities are chosen for each supplier in the supply chain. Those activities are as follows: (1) improve the existing supplier ($k = 1$), (2) replace the existing supplier with a new and improved supplier ($k = 2$), (3) increase the firm's oversight at the existing supplier ($k = 3$), or (4) take no mitigation activity at all ($k = 4$). The specific investment costs for each activity and the assumed improvement of the supplier as a result of taking the respective mitigation action can be found in Table 3.5. Optimal mitigation activities chosen for the steam turbine thrust bearing supply chain are shown in Figure 3.17.

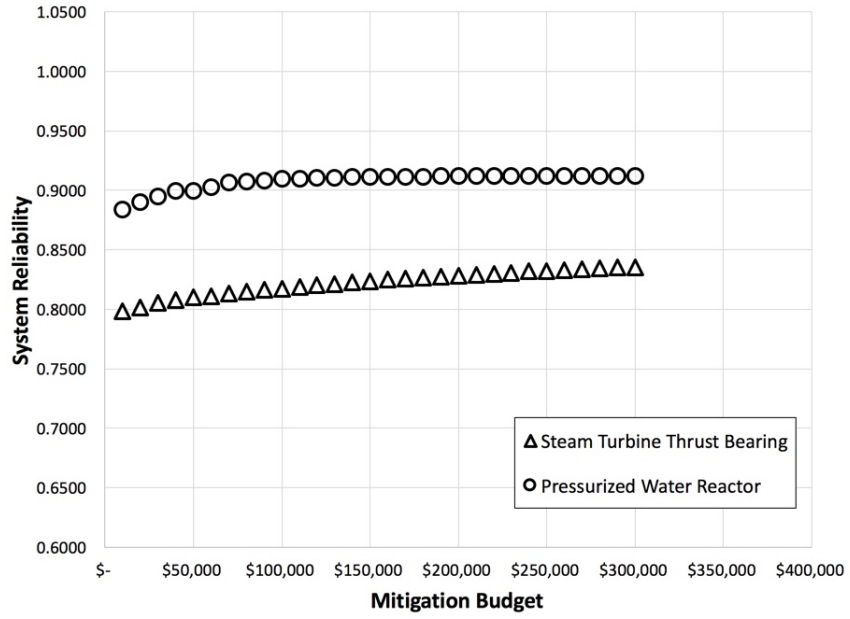
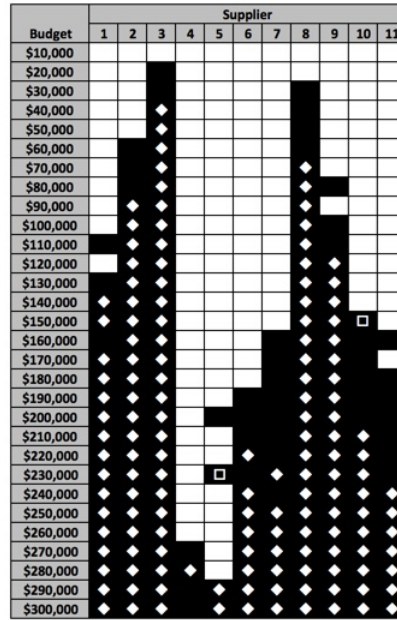
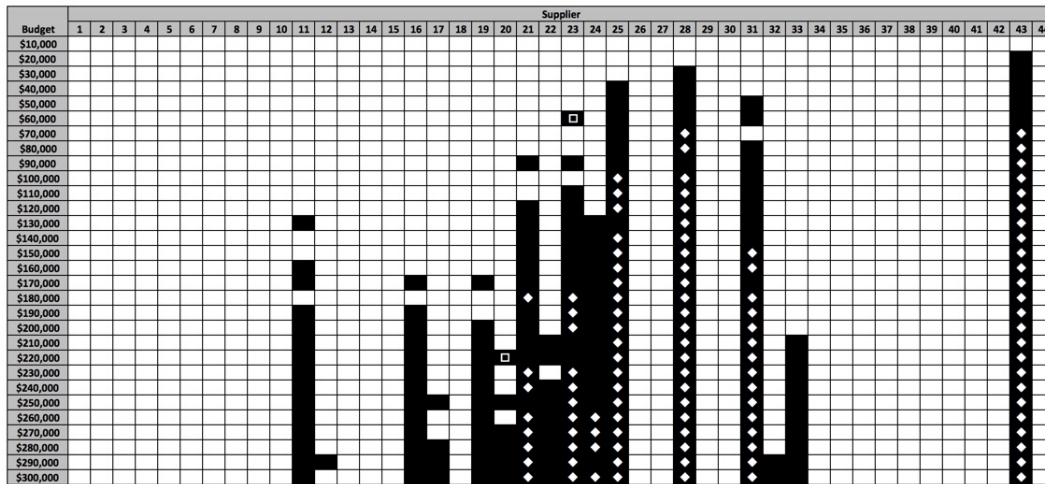


Figure 3.16: System reliability improvement as a function of mitigation cost (imperfect mitigation model).

k	Symbol	Mitigation
1		Improve the existing supplier
2	◆	Replace the existing supplier with new supplier
3	□	Increase oversight at existing supplier
4		No mitigation activity



(a) Pressurized water reactor.



(b) Steam turbine thrust bearing.

Figure 3.17: Mitigation activities selected as a function of mitigation budget.

Similar to the perfect mitigation model, the tradeoff between mitigation investment and improvement in overall supply chain system reliability is useful to a practitioner. Compared to the perfect mitigation model, the imperfect mitigation model provides additional flexibility since mitigation activities for individual suppliers are chosen by the model. As a result, improvements in system reliability based on specific actions are observed up to the maximum budget allocated (\$300,000) and the practitioner is left to decide if the incremental investment is worth the additional improvement.

The additional flexibility that the imperfect mitigation model provides a supply chain practitioner is evident in the activities chosen by the model. Generally, if mitigation funds are available, the model seeks to maximize the use of those funds for a corresponding maximum benefit in system reliability. As a result, the mitigation activities chosen and the suppliers chosen to mitigate change at increasing budgetary levels depending on the cost-reliability tradeoff; a pattern that is observed in both the pressurized water reactor and steam turbine generator supply chains.

3.5.3 Comparison of Mitigation Models and Formulations

When comparing the supply chain system reliabilities generated by the perfect and imperfect mitigation models, the differences can be attributed to the underlying models. More specifically, the perfect mitigation model uses a fault tree and subsequently minimal cut sets as its basis. Consequently, the assumptions that underly fault trees and the Boolean algebra used to calculate the top event reliabilities are also assumed in the perfect mitigation model. The differences observed in our computational examples are practicable

and compare reasonably well with what has been reported in the literature where comparisons between fault trees to binary decision diagrams are discussed [143]. Table 3.6 shows a summary of the system reliability values calculated for each of the supply chains studied and the respective mitigation model prior to any mitigation activities being taken. For comparison purposes, the respective system reliabilities calculated using the rare event approximation are also included.

Table 3.6: Comparison of system reliability for perfect and imperfect mitigation models (no mitigation).

Description	Pressurized Water Reactor	Steam Turbine Thrust Bearing
Rare Event Approximation (\mathcal{R}_S^{REA})	0.8785	0.6871
Perfect Mitigation Model (\mathcal{R}_S^{PMM})	0.8837	0.7275
Imperfect Mitigation Model (\mathcal{R}_S^{IMM})	0.8836	0.7982

Although the perfect mitigation model provides less information to the practitioner than the imperfect mitigation model, it can be notionally useful to identify areas of concern (suppliers to focus on when planning mitigation efforts) within the supply chain. Once those areas of concern are identified, the practitioner may chose the specific mitigation activities to perform for each individual supplier.

Next, we compare the two mitigation models by analyzing the solution sets at the same budgetary levels and the system reliabilities at the same budgetary levels for each of the supply chain systems studied. The perfect mitigation model contains two decision variables, x_i and y_j , which represent the cut sets containing suppliers and the suppliers chosen

at each mitigation budget level respectively. As a result, we are able to compare the solution sets of suppliers selected for the perfect and imperfect mitigation models for each budgetary level. Figure 3.18 includes the results of the solution set comparison for both supply chains studied. Table 3.7 summarizes the comparison of the frequency by which suppliers were selected by each mitigation model for each of the supply chains. Overall, the models vary considerably with respect to the suppliers selected for mitigation. It's worth noting that the perfect mitigation model for the pressurized water reactor supply chain reached 100% reliability at a budgetary level of \$100,000. Therefore, comparisons of the two models at budgetary levels greater than \$100,000 are not valid. Across both supply chains, certain suppliers appear to be preferred by one or both of the mitigation models. For example, Supplier 3 is selected by both the perfect and imperfect mitigation models consistently in the pressurized water reactor supply chain up to a budgetary level of \$110,000. Similarly, Supplier 28 is selected by both mitigation models in the steam turbine thrust bearing supply chain up to a budgetary level of \$300,000. In both supply chains, Supplier 3 and Supplier 28 represent suppliers with lower reliabilities in comparison to other suppliers. From these general trends, it appears that there is a preference to select suppliers for mitigation that will have the largest contribution to maximizing the reliability of the respective supply chain portfolio.

Table 3.7: Frequency of supplier selection by each mitigation model.

Supplier selected by	Pressurized Water Reactor	Steam Turbine Thrust Bearing
Only the perfect mitigation model	20	132
Only the imperfect mitigation model	0	8
Both the perfect and imperfect mitigation models	29	233
Neither the perfect nor imperfect mitigation model	72	947
Total number of mitigation opportunities	121	1320

To compare the system reliabilities for each budgetary level, we introduce a metric, ρ , that we define as $\left| \frac{\mathcal{R}_S^{PMM} - \mathcal{R}_S^{IMM}}{\mathcal{R}_S^{PMM}} \right|$ where \mathcal{R}_S^{PMM} is the system reliability for the perfect mitigation model and \mathcal{R}_S^{IMM} is the system reliability for the imperfect mitigation model at each budget level for the respective supply chain being analyzed. A summary of results is presented in Figure 3.19. In general, ρ increases for each supply chain with increasing budget levels with the exception of $STTB$, which decreases from 9.6% at a mitigation budget of \$10,000 to 0.8% at \$30,000 and then increases at successive budget levels with a few exceptions. Overall, ρ_{PWR} increases with increasing mitigation budgets with a few exceptions. Thus, across the range of mitigation budgets inspected, the two mitigation models diverge from one another with increasing budget and appear to converge to a relatively constant value of $\rho_{PWR} \approx 9.0\%$ and $\rho_{STTB} \approx 16.5\%$ for each of the respective supply chains. These results are important for the practitioner to understand if both mitigation models are used and subsequently compared to one another. In addition, the practitioner

should be aware of how the difference between the two models stabilizes only at higher budgetary levels.

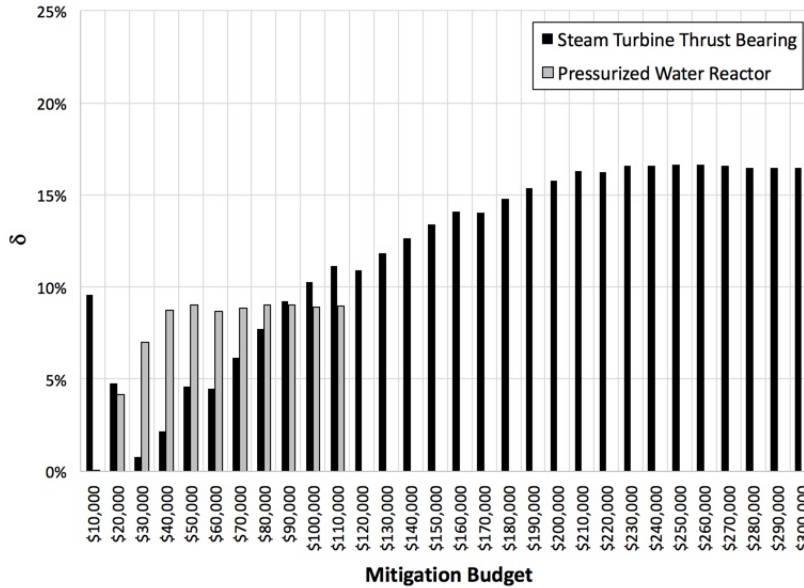


Figure 3.19: Comparison of perfect and imperfect mitigation model system reliabilities.

In general, the solution times observed for all models, formulations, and supply chains were as expected in that the linearized formulations (Eq. (3.2)-(3.4) and (3.8)-(3.13)) converged to a solution quicker than the nonlinear formulations (Eq. (3.1)-(3.4) and Eq. (3.5)-(3.7)) and the pressurized water reactor supply chain containing fewer nodes (i.e., suppliers) had solution times that were less than those of the larger steam turbine thrust bearing supply chain. Overall, the steam turbine generator supply chain, which consists of 44 suppliers took longer to solve than the pressurized water reactor supply chain, which has 11 suppliers. Additionally, the nonlinear formulation took longer to solve than the

linearized formulation. Lastly, overall the perfect mitigation model solved more quickly than the imperfect mitigation model and the majority of the models contained within the computational study converged on the optimal solution within a maximum of a few minutes with few exceptions. Table 3.8 shows the solution times as a function of the budgetary levels at which the respective models were run and provides summary statistics for each model, formulation, and supply chain combination. When applied to larger supply chain systems, faster computation time may be beneficial to the supply chain professional. As a result, depending on the objective of the analysis, the perfect mitigation model may be most advantageous. However, if the details provided by the imperfect mitigation model are required, the linearized form of the model would most likely be preferred due to its improved computational efficiency over the nonlinear formulation.

Table 3.8: Summary of solution times.

	Perfect Mitigation Model				Imperfect Mitigation Model			
	Nonlinear		Linear		Nonlinear		Linear	
	Bonmin		CPLEX		Bonmin		CPLEX	
	PWR	STTB	PWR	STTB	PWR	STTB	PWR	STTB
\$10,000	0.000	0.00	0.000	0.000	0.89	66.59	0.00	0.00
\$20,000	0.284	18.80	0.002	0.012	3.03	107.67	0.02	0.97
\$30,000	0.158	9.62	0.007	0.010	2.63	114.95	0.05	5.40
\$40,000	0.131	9.72	0.008	0.010	1.54	102.97	0.05	7.11
\$50,000	0.204	12.05	0.010	0.016	7.13	47.00	0.14	15.14
\$60,000	0.240	43.25	0.010	0.009	3.30	309.27	0.09	27.57
\$70,000	0.234	55.24	0.006	0.010	2.85	341.24	0.08	35.07
\$80,000	0.193	36.91	0.006	0.009	5.61	112.60	0.06	48.31
\$90,000	0.045	11.87	0.006	0.010	4.00	291.24	0.11	61.18
\$100,000	0.079	13.29	0.003	0.010	2.56	673.47	0.11	69.92
\$110,000	0.015	13.62	0.002	0.010	3.48	406.68	0.12	58.99
\$120,000	-	1272.18	-	0.010	4.66	229.14	0.11	127.59
\$130,000	-	645.30	-	0.007	0.95	436.55	0.12	91.09
\$140,000	-	246.02	-	0.007	1.15	509.40	0.11	90.47
\$150,000	-	108.21	-	0.011	3.52	191.66	0.15	73.12
\$160,000	-	53.29	-	0.007	7.60	154.08	0.16	111.96
\$170,000	-	5944.49	-	0.009	3.45	617.86	0.39	122.44
\$180,000	-	273.51	-	0.009	3.38	2064.43	0.18	156.72
\$190,000	-	29.10	-	0.007	0.63	1216.15	0.18	126.77
\$200,000	-	18.47	-	0.020	3.47	359.67	0.19	94.15
\$210,000	-	10.31	-	0.007	5.88	80.62	0.18	133.09
\$220,000	-	14.01	-	0.007	0.31	3480.11	0.16	187.96
\$230,000	-	20.60	-	0.007	4.29	439.12	0.14	112.24
\$240,000	-	51.42	-	0.007	1.29	147.21	0.14	151.75
\$250,000	-	13.98	-	0.009	0.58	359.57	0.10	312.28
\$260,000	-	6.92	-	0.007	3.97	509.15	0.09	184.43
\$270,000	-	7.30	-	0.008	4.35	210.55	0.13	147.36
\$280,000	-	60.19	-	0.007	0.21	148.24	0.07	173.06
\$290,000	-	41.02	-	0.008	0.32	314.08	0.08	255.75
\$300,000	-	35.55	-	0.007	0.68	1646.63	0.08	164.79
Average	0.14	302.88	0.01	0.01	2.92	522.93	0.12	104.89
Standard Deviation	0.09	1095.28	0.00	0.00	1.99	711.31	0.07	74.44
Maximum	0.28	5944.49	0.01	0.02	7.60	3480.11	0.39	312.28
Minimum	0.00	0.00	0.00	0.00	0.21	47.00	0.00	0.00

3.6 Conclusions and Managerial Insights

The approach outlined in this research solves many of the supply chain risk mitigation decisions that face a practitioner in a LVHV supply chain. Mitigation decisions are typically made in silos and in a vacuum without full perspective of the impact that the respective decisions may have on the supply chain or the firm in general. In practice, multiple variables play a role in these types of decisions and coalescing the requisite information together in a timely fashion is a challenge. Further, experience is commonly used over quantitative analysis and can be inherently biased. Because our approach links the bill of materials being sourced by modeling the supply chain system as a fault tree, the practitioner is enabled with a quantitative decision tool that takes into account the impact that an individual mitigation decision can have on the overall reliability of the supply chain being analyzed. In addition, the data used within the models presented is available to most managers, which makes the approach practical to implement.

All too often, reactionary decision making is common in supply chain management and resources are consumed in the associated activities. The methods described in this research enable the supply chain practitioner to conduct scenario analysis to determine which supply chain structures pose the greatest risk and highest costs to manage. Examples of scenarios that can be analyzed include, but are not limited to supplier selection, the use of single or sole sources of supply, and the impact of redundant sources of supply. In addition, the supply chain models can be updated to reflect the actual performance of suppliers. As

a result, the supply chain professional may choose to reallocate resources to individual suppliers in order to further mitigate risk within the supply chain for orders that have not yet been fulfilled.

As noted, many decisions are based on experience, which is valuable, but can be flawed. The data required in the models described is collected by most firms and is readily available via their respective enterprise resource planning systems. As a result, practitioners can utilize available data to make more quantitatively informed decisions, which can be supplemented by experience. For example, if run at various budgetary levels the imperfect mitigation model will return a set of supply chain system reliabilities. The practitioner can then use their experience and knowledge of the respective organization to make a tradeoff between the mitigation costs and improved reliability provided by the Pareto set.

We compared both the results and run times of the imperfect and perfect mitigation models presented. As expected, the linearized formulations of both models demonstrated quicker solution times than their nonlinear counterparts. Further, the steam turbine thrust bearing supply chain had slower solution times as expected due to it having more suppliers (44) than the pressurized water reactor supply chain (11).

Even though the model is more complex, the imperfect mitigation model is more practical to implement as it provides provides specific mitigation activities for the the user to consider. Despite the fact that only four mitigation options were presented in this research, additional mitigation options can be added with relative ease to the imperfect mitigation model and customized to the individual needs of the firm.

The research presented herein advanced the use of fault tree analysis to represent a supply chain based on the bill of materials of a product or service procured [105]. Our approach provides a portfolio of risk mitigation activities that minimize supply chain risk while simultaneously achieving the budgetary constraints of the firm. Furthermore, the technique is applicable to all levels of the supply chain and viewpoints from within the supply chain. We demonstrated this by taking the perspective of a firm constructing a nuclear power plant as well as a lower-tier firm within the supply chain that manufactures a thrust bearing that will be supplied within a critical assembly installed in the power plant.

Several areas of future work are planned. First, our modeling approach only accounts for the reliability of the suppliers within the supply chain and addresses neither the severity nor the impact of a delay that may result from a supplier having less than 100% reliability. Extending the models to account for the impact that a risk may have if realized as well as the associated downtime is useful.

In addition, our approach assumes that supplier data is known at the time the model is built. In practice, this is not always the case and is most notable for new suppliers that the firm has no prior history with. We plan to develop a multiple logistic regression model to estimate the reliability of a supplier. In order to do so, it is important to understand the explanatory variables that correspond to supplier reliability. Once built and implemented in practice, such a model can leverage machine learning methodologies to better tune the model as well as provide additional insights into the factors that affect supplier reliability. By developing predictive models, we will be able to relax the independence assumption utilized in this research and begin to integrate risks shared by suppliers within a supply

chain. Examples of such risk factors include natural disasters such as hurricanes, which are geographically and seasonally dependent.

CHAPTER 4
PREDICTING SUPPLIER RELIABILITY IN A LOW VOLUME HIGH VALUE
SUPPLY CHAIN

4.1 Introduction

Over the past several years, manufacturing firms have unbundled, outsourced, offshored, globalized, and fragmented [153]. Benefits of these actions include cost reduction, a better focus on core competencies, access to suppliers with economies of scale and specialized process knowledge, the ability to leverage existing capital investments, increasing capacity flexibility, and transferring uncertainty [154]. However, new challenges have resulted. One such challenge is the ability to efficiently and effectively coordinate multiple firms' activities across the supply chain. This lack of coordination is common and can result in unplanned disruptions and delays. According to Deloitte [155], 85% of global supply chains experienced at least one disruption in the past 12 months. However, companies that proactively manage supply chain risk were found to have spent 50% less to manage supplier disruptions than companies that stated they aren't proactive.

Proactive supply chain risk management is a complex activity because of silos between organizations, misaligned incentives, inefficient reporting structures, insufficient processes, and the scarcity of simple tools for professionals to use. Quite simply, although important, proactive supply chain management is difficult. As a result, it is a rarely applied

strategy within firms. According to Juttner et al. [6], what seems to be missing is a more proactive approach where risk implications are anticipated at an earlier stage. In March 2000, a Philips semiconductor plant caught fire and resulted in a shortage of supply to both Ericsson and Nokia. The disruption impacted the two companies very differently. Philips was able to increase production at an alternative supplier and suffered little financial impact. Ericsson on the other hand had taken on a single-source strategy and led to a loss of more than \$400 million in potential revenue. [69]

Industry examples like the fire experienced within the Ericsson and Nokia supply chains points to a need to better understand the potential consequences of taking on a single-source strategy. The ability to identify and mitigate risks within supply chains is of the utmost importance to both practitioners and researchers because of the potential for unfavorable consequences to a firm's financial performance should those risks be realized [156]. As a result, supply chain risk management is a field of increasing importance [45].

The need for proactive supply chain risk management is an important endeavor regardless of the volume being produced by the firm. However, the challenges faced by low volume industries and high volume industries can be different. For example, firms that participate in higher volume industries such as those that support automotive and consumer markets have several contract manufacturers with relatively equivalent capabilities to procure from. In addition, products are relatively low cost and are made-to-stock. Inventory is maintained and optimized to provide a buffer against delays and any disruptions that may occur within a supply chain. Multiple inventory locations may also be possible due to a wide distribution network as well as the volume moving across the supply chain. Diverse

inventory locations and transportation networks can subsequently be leveraged to mitigate localized disruptions in the supply chain should a disaster occur. As a result of the demand generated in these higher volume industries multiple sources of supply are typical and provide an opportunity for a firm to diversify purchase order placements and mitigate against the risks that may result from any one firm within the supply chain.

Many of these risk mitigation strategies are not afforded to lower volume industries. Instead, firms that participate in lower volume industries typically have low (if any) inventory levels and single sources of supply. Companies that support the construction of nuclear power plants are an example of a low volume industry. Instead of producing millions of products each year, the demand created when a new nuclear power plant is constructed may only require a firm within the supply chain to produce 10 or so items over the course of 1-2 years. Although the associated production volume of products supporting the industry are typically low, the selling price for critical items may be quite high (on the order of hundreds of thousands or millions of dollars per unit). The higher value of the products being sourced in combination with fewer suppliers and lower quantities adds to the risk within the supply chain and necessitates a higher degree of reliability.

Aside from the severity of adverse events that may result from nuclear energy should a nuclear event occur, several factors exist that make nuclear energy a cost prohibitive solution. In addition to low volumes and somewhat sporadic demand, the strict requirements and high standards required to enter the nuclear supply chain cause many suppliers to avoid the industry altogether. In turn, companies responsible for constructing and maintaining nuclear power plants are faced with a limited supply base to produce critical, large, and ex-

pensive items. The quality and reliability of these items are essential to the safe operation of the nuclear power plant. In addition, firms are faced with the financial consequences of delays in the delivery of these products to the construction site. Losses incurred by the power plant owner as a result of delays are estimated at \$1.2 million per day [149] and can lead to liquidated damages being levied on suppliers. Although nuclear power capacity is increasing steadily with about 50 reactors under construction globally most of the power reactors currently planned or under construction are in Asia. As a result of a real or perceived imbalance between the costs and risks associated with nuclear power, new power plant construction has slowed in the United States. The last nuclear power plant to be commissioned in the United States was the Watts Bar plant, which was constructed from 1973-1990 and became operational in 1996. (www.world-nuclear.org)

In March 2013, construction began on a total of four new nuclear reactors in the United States with two being constructed at the Virgil C. Summer Nuclear Generating Station site near Jenkinsville, SC and two at the Vogtle Electric Generating Plant site in Burke County, GA. Since construction began, both locations have experienced significant delays. In 2014, the industry identified two primary challenges for nuclear power to remain competitive: (1) ensure that the economics of nuclear power are competitive with other generating sources and (2) maintain a reliable international supply chain that is capable of delivering high quality products [3]. In the summer of 2017 construction at the Virgil C. Summer site was abandoned due to a number of factors, including the deterioration of a “robust supply chain” within the industry over the past 30 years [150].

The ability to identify and mitigate risks within supply chains, whether supporting high or low volume industries, is of the utmost importance to both practitioners and researchers because of the potential for unfavorable consequences to a firm's financial performance should those risks be realized [156]. As a result, supply chain risk management is a field of increasing importance [45]. Although much has been published in the domain, few studies have quantitatively identified the specific factors that affect supply chain risk. Some authors have broadly categorized the types of supply chain risks in terms of whether or not the risk occurs *internally* or *externally* to the firm or supply chain [8, 157, 158, 159] as well as whether or not the risk is *controllable* or *not controllable* [157]. Ho et al. [9] categorizes risk factors as being *macro* or *micro* in nature. Examples of macro factors include natural disaster, war, terrorism, and political environment [112, 39, 157]. Micro factors include risks associated with demand, manufacturing, supply, information, transportation, and finance.

In practice, firms that actively manage supply chain risk utilize a variety of tools to estimate the probability of a disruption and the factors that affect risk. Most are based on historical performance, are isolated to individual measures, and few are quantitative. Examples of methods include qualitative rating systems (high, medium, low), weighted averages or compilations of supplier metrics (on-time delivery, first-time quality, etc.), and hazard matrices. Although these types of methods can be directionally effective, little research rigorously validates their performance in actually improving risk management decisions [2]. In addition, the application of these methods have poor resolution, do not always provide clear direction, are inconsistent over the course of time, and can be fraught with

the biases of the individuals performing the rating or applying weights to the quantitative measures. Subsequently, poor decision making can result when based on these techniques.

Deploying more sophisticated quantitative modeling techniques that utilize machine learning algorithms can be more difficult to implement in practice. However, these techniques can provide a significantly more objective view of a firm's supply chain risk than the qualitative rating systems frequently employed. In this research, we overcome this barrier by demonstrating a methodology that applies available techniques to a LVHV firm's supply chain data set.

With respect to risk identification in supply chains, most research focuses on higher volume industries such as automotive and consumer packaged goods and not on LVHV industries like nuclear power plant construction [11, 12, 13, 14, 15, 16]. Furthermore, few if any comprehensive quantitative studies based on empirical data have been conducted to determine the factors that affect supply chain reliability. In this research we address this gap by proposing a multinomial logistic regression machine learning model based on actual industry data with the purpose of predicting the reliability of sourcing a product within the nuclear power plant construction industry.

We use The American Production and Inventory Control Society's (APICS) Supply Chain Operations Reference (SCOR[®]) Model as a basis for our definition of reliability and as the dependent variables in the proposed models. The SCOR[®] Model was developed by practitioners and is an industry-respected guide to improve the performance of supply chain processes within organizations [160]. The SCOR[®] Model proposes a set of performance attributes, which are a grouping of metrics. The performance attributes are (1) reliability,

(2) responsiveness, (3) agility, (4) cost, and (5) asset management efficiency. Reliability is defined as “perfect order fulfillment” and consists of four metrics. These metrics include (1) the percentage of orders delivered in full, (2) delivery performance to customer commit date, (3) documentation accuracy, and (4) perfect condition. As a result of the data available, the proposed model aims to predict reliability in terms of three of the four metrics: (1) delivery performance to customer commit date (on-time), (2) documentation accuracy (perfect documentation), and (3) perfect condition (perfect quality). Logistic regression is an appropriate method given that we are predicting the probability of success of a system based on a number of factors. The resulting model has practical implications for supply chain professionals in that it can be used to compare the reliability of suppliers during the supplier selection process or as input to predicting the reliability of a given supply chain system [161].

We categorize the explanatory variables in the model as being supplier-specific, purchase-specific, or item-specific. Supplier-specific variables include attributes inherent to an individual supplier such as core competency, quality program sophistication, and size of the firm. Regional factors that affect a supplier’s reliability may be shared by multiple suppliers simultaneously and include the susceptibility to natural disasters, government unrest, and transportation challenges. Because this information wasn’t readily available in the data sets used for this research, we have chosen to use supplier location data (country, state, postal code) as a proxy. Purchase-specific variables include such factors as the quality requirements imposed on the supplier, whether or not the purchase was made generically or for a specific product that the firm manufactures, the timing of the purchase, expected

lead time, and the value of the order. The third type of explanatory variables investigated are those that are specific to the item or service being procured. Examples of this type of variable include the type of item (casting, forging, etc.) being procured, the level of quality required, and the value of the item to name a few.

This research makes key contributions to the current literature on supply chain risk management in that we propose an implementable method to quantify procurement risks. Specifically, we develop a multiple logistic regression model to predict the reliability of a procurement in a LVHV supply chain. We confirm our model using 10-fold cross validation and assess the results using a set of performance metrics. Lastly, we test the significance of explanatory variables within the model and draw conclusions about the underlying data set based on the observed results. The proposed method improves upon existing qualitative methods and provides a framework for practitioners to improve proactive decision making by predicting the reliability of a procurement.

The remainder of this chapter is organized as follows. Section 4.2 describes the data and variables used to build the model. The methodology used is found in Section 4.3. In Section 4.4, we analyze the numerical results of the model and draw conclusions in Section 4.5.

4.2 Data Description

The data used in this model is actual data collected within a firm's enterprise resource planning (ERP) system. The data set includes a total of 3,784 shipments on 2,928 purchase order (PO) line items received from 157 suppliers across one full calendar year and is rep-

representative of a typical year for the firm. In total, 42 explanatory variables are included in building the models within the scope of this research. Explanatory variables were selected based on practitioner knowledge as well as availability within the ERP system. Each of the explanatory variables are organized into one of three groups: (1) supplier-specific (supplier), (2) purchase-specific (purchase), and (3) item-specific (item). Supplier-specific variables are representative of factors specific to the firm providing the good or service. Examples include the quality program qualifications that the firm holds, the firm's geographic location (state, country), and the volume of sales the firm has received from the supplier. Factors associated with the specific purchase order represent purchase-specific variables and include the quality requirements imposed on the purchase order, the quantity of items or services included on the purchase order, and the expected lead time for the purchase order. Item-specific variables include those elements that are associated with the item or service being purchased. Examples include the product family to which the item or service belongs, the program that the item or service is being purchased for, and the activities that the firm will be requested to perform in order to provide the item or service. Seventeen variables comprise the supplier grouping, 18 are included in the purchase group, and seven variables are incorporated in the item group. A description of each variable within its respective group is included in Tables 4.1- 4.3 along with the variable's type and the number of levels (if a binary or categorical variable) that comprise each.

Table 4.1: Description of explanatory variables related to the supplier.

<i>i</i>	Definition	Type	Levels
1	Supplier: The supplier providing the firm the good or service.	Categorical	158
2	PO Line Items: The number of line items received from a respective supplier within the current year and prior three years.	Discrete	-
3	POs: The number of purchase orders received from a respective supplier within the current year and prior three years.	Discrete	-
4	Rework POs: The number of purchase orders received with rework completed by the respective supplier within the current year and prior three years.	Discrete	-
5	Level 1 Qualifications: The total number of the most rigorous quality program qualifications that the respective supplier has been qualified to by the purchaser (example: ASME code, etc.).	Discrete	-
6	Level 2 Qualifications: The total number of the second most rigorous quality program qualifications that the respective supplier has been qualified to by the purchaser (example: 10CFR50 App B, 10CFR21, welding, non-destructive examination, etc.).	Discrete	-
7	Level 3 Qualifications: The total number of the third most rigorous quality program qualifications that the respective supplier has been qualified to by the purchaser (example: ISO 9001, MIL-STD, etc.).	Discrete	-
8	Level 4 Qualifications: The total number of the second least rigorous quality program qualifications that the respective supplier has been qualified to by the purchaser (example: qualified questionnaire, data assessment, etc.).	Discrete	-
9	Level 5 Qualifications: The total number of the least rigorous quality program qualifications that the respective supplier has been qualified to by the purchaser (example: no quality program required).	Discrete	-
10	Highest Qualification: The most rigorous quality program qualification to which the respective supplier has been qualified by the purchaser (Level 1=Most, Level 5=Least).	Discrete	-
11	Lowest Qualification: The least rigorous quality program qualification to which the respective supplier has been qualified by the purchaser (Level 1=Most, Level 5=Least).	Discrete	-
12	Qualification Range: The difference between the most rigorous and least rigorous quality program qualification to which the respective supplier has been qualified by the purchaser (Level 1=Most, Level 5=Least).	Discrete	-
13	Qualifications: The total number of quality program qualifications to which the respective supplier has been qualified by the purchaser.	Discrete	-
14	Core Competency: The defining capability with regard to a product or service that the respective supplier provides the purchaser.	Categorical	36
15	Country: The country where the respective supplier is located.	Categorical	9
16	State: The state, if within the United States, where the respective supplier is located.	Categorical	29
17	Sales: The total value of all purchase orders provide by the respective supplier to the purchaser within the current year and prior three years combined.	Continuous	-

Table 4.2: Description of explanatory variables related to the purchase order.

<i>i</i>	Description	Type	Levels
18	Expected Lead Time: The number of days between the date that the contract was placed and the expected contractual date of receipt.	Discrete	-
19	Expected Receipt Date: The expected date of receipt.	Discrete	-
20	Date PO Line Created: The date that the purchase order line item was initiated to the respective supplier.	Discrete	-
21	PO Line Quantity: The quantity of products/services on the respective purchase order line item that the respective supplier is expected to deliver.	Discrete	-
22	Multiple Receipts per Line: Designation of whether multiple shipments were received by the purchaser associated with each purchase order line item placed to the respective supplier.	Discrete	-
23	Rework: Designation of whether or not the purchase order line item required rework activities at the respective supplier.	Binary	2
24	Quarter and Year of Receipt: The quarter and year that the shipment was received by the purchaser from the respective supplier.	Discrete	-
25	Month and Year of Receipt: The month and year that the shipment was received by the purchaser from the respective supplier.	Discrete	-
26	Level 1 Qualification Requirements: The total number of the most rigorous quality program requirements contained within the purchase order (example: ASME code, etc.). These purchase order requirements correspond to the qualifications of the respective supplier (Level 1 Qualifications).	Discrete	-
27	Level 2 Qualification Requirements: The total number of the second most rigorous quality program requirements contained within the purchase order (example: 10CFR50 App B, 10CFR21, welding, non-destructive examination, etc.). These purchase order requirements correspond to the qualifications of the respective supplier (Level 2 Qualifications).	Discrete	-
28	Level 3 Qualification Requirements: The total number of the third most rigorous quality program requirements contained within the purchase order (example: ISO 9001, MIL-STD, etc.). These purchase order requirements correspond to the qualifications of the respective supplier (Level 3 Qualifications).	Discrete	-
29	Level 4 Qualification Requirements: The total number of the least rigorous quality program requirements contained within the purchase order (example: qualified questionnaire, data assessment, etc.). These purchase order requirements correspond to the qualifications of the respective supplier (Level 4 Qualifications).	Discrete	-
30	Highest Qualification Requirement: The most rigorous quality program requirement contained within the purchase order (Level 1=High, Level 5=Low).	Discrete	-
31	Lowest Qualification Requirement: The least rigorous quality program requirement contained within the purchase order (Level 1=High, Level 5=Low).	Discrete	-
32	Qualification Requirements: The total number of quality program requirements contained within the purchase order.	Discrete	-
33	Quality Requirements: The total number of quality requirements (in addition to quality program requirements) contained within the purchase order (example: dimensional, inspection, documentation, etc.).	Discrete	-
34	Program Family or Generic: The designation of whether or not the purchaser has assigned the item or service being purchased to a product line for consumption after receipt.	Binary	2
35	Value: The total amount paid by the purchaser for the respective item or service associated with an individual purchase order and line item.	Discrete	-

Table 4.3: Description of explanatory variables related to the item being purchased.

<i>i</i>	Definition	Type	Levels
36	Commodity: The primary coding system used by the firm to group the item/service being procured.	Categorical	40
37	Item/Service Identifier: A coding system used by the firm to identify complexity of the item or service being procured (example: assembly, raw material, etc.).	Categorical	10
38	Item Family: A secondary coding system used by the firm to group the item/service being procured.	Categorical	40
39	Service Family: Similar to the commodity coding system, an identifier that groups the item being procured into families of procurements.	Categorical	24
40	Program: The designation that the purchaser has assigned the item or service being purchased that describes the specific product line that will use the procurement.	Categorical	54
41	Program Family: The designation that the purchaser has assigned the item or service being purchased that describes the family of product lines that will use the procurement.	Categorical	9
42	Activities: The total number of activities that the supplier will be asked to perform regarding the item or service being procured on an individual purchase order.	Discrete	-

We incorporate all 42 explanatory variables into seven full training models. Each of the seven models utilizes a dependent variable that represents one or more than one of the combinations of the three measures that comprise reliability as defined by the SCOR[®] model. The dependent variables are binary variables and represent whether or not an item or service associated with a purchase order line item was delivered (1) on-time to the respective contractual delivery date, (2) with perfect documentation accuracy the first time, and/or (3) with perfect quality the first time. Table 4.4 summarizes the seven combinations of the dependent variables that represent reliability as well as the aggregated favorable (reliable) and unfavorable (unreliable) responses of each across the data set used. Figure 4.1 summarizes the distribution of supplier performance for the seven reliability metrics.

Table 4.4: Summary of reliability metrics.

Model (r)	Reliability Metric / Dependent Variable	Reliable	Unreliable	n
1	On-Time	91.70%	8.30%	3,784
2	Perfect Documentation	65.38%	34.62%	3,784
3	Perfect Quality	89.30%	10.70%	3,784
4	On-Time + Perfect Documentation	62.00%	38.00%	3,784
5	On-Time + Perfect Quality	82.21%	17.79%	3,784
6	On-Time + Perfect Quality + Perfect Documentation	56.71%	43.29%	3,784
7	Perfect Quality + Perfect Documentation	59.62%	40.38%	3,784

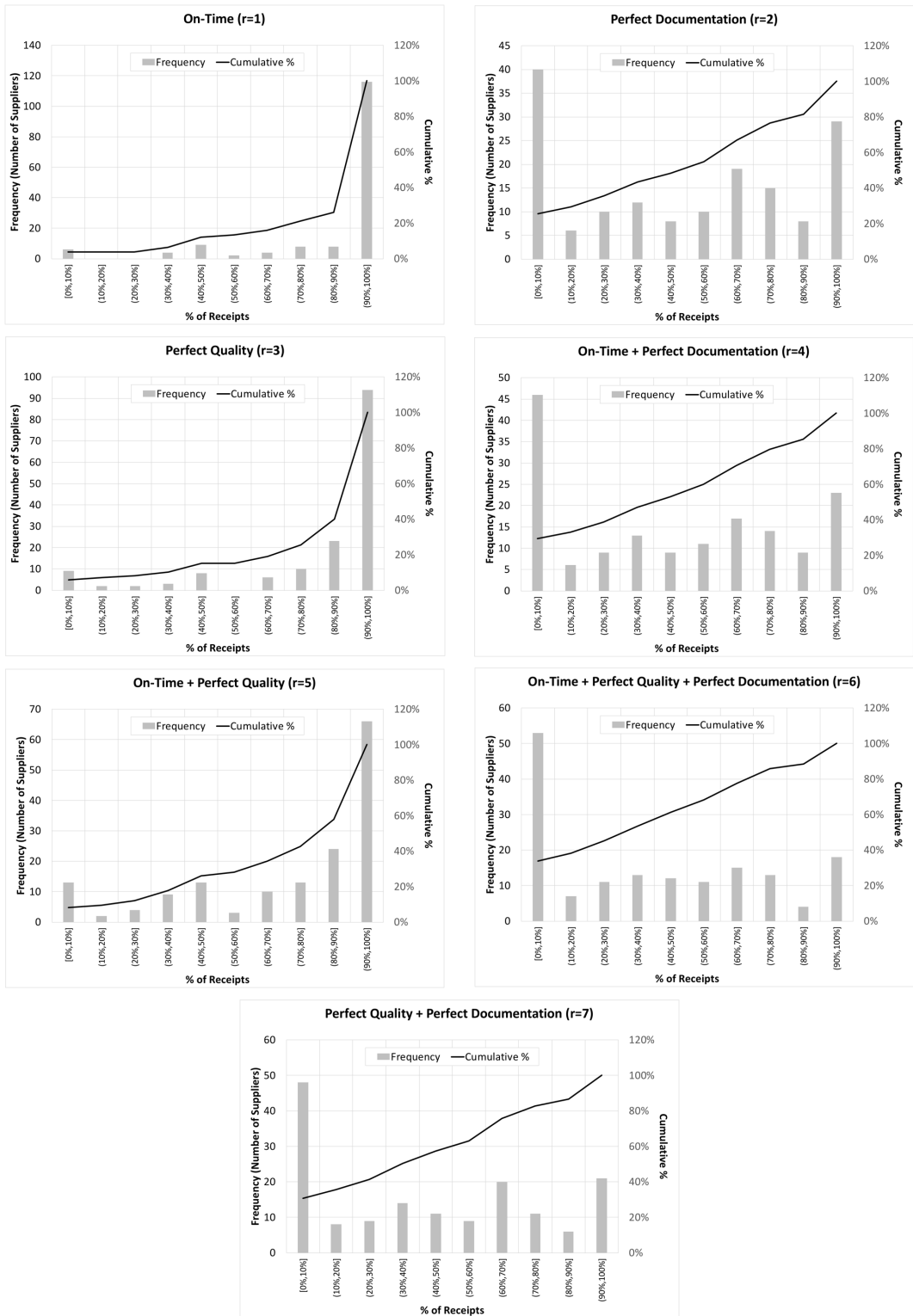


Figure 4.1: Supplier reliability distributions.

4.3 Methodology

To prepare the master data set, we joined a number of data tables within the firm's ERP system to arrive at the set of dependent and independent variables to test for significance within the model. Initially, data sets representing multiple years of transactions were analyzed. However, after reviewing the data available, we determined that one year of data was sufficient to test and build the intended models with consideration for a reasonable amount of computing time. Next, we performed a summary analysis on the data set across the dependent variables to better understand the patterns in the underlying data. In each of the dependent variables, the two classes (reliable and unreliable) were found to be imbalanced and not represented equally. Imbalanced data sets can cause problems for data mining and statistical learning since traditional machine learning algorithms have a tendency to classify data points in the class that occurs most frequently [162]. Several methods have been proposed to deal with imbalanced data sets and include random over-sampling, random under-sampling, Tomek links, condensed nearest neighbor rule, one-sided selection, neighborhood cleaning rule, synthetic minority over-sampling technique (SMOTE), and hybrids of these approaches [163]. Other authors have reported that one holdout sampling method, k -fold cross-validation, is the best method to use for model selection when applied to real world data sets and when imbalanced data sets are involved [164]. More specifically, 10 seems to be an optimal number of folds when trying to optimize the time it takes to complete a test while at the same time minimizing the bias and variance associated with

the validation process [165]. As a result, we chose to employ 10-fold cross validation to validate the predictor variables within our model and as the standard way to predict the error rate of our model.

In 10-fold cross validation, the data set is divided into 10 parts in which the class is represented in approximately the same proportions as in the full dataset. Next, the model, in our case a logistic regression model, is fit on the training set (nine-tenths of the data) and then tested on the test set (one-tenth of the data set). Each of the 10 parts is then held out in turn and the model trained on the remaining nine-tenths. The error rate is then calculated on the test set. The experiment is repeated 10 times. As a result, the model is built a total of 10 times on different training sets and tested using 10 test sets. Finally, the 10 error estimates are averaged to yield an overall error estimate. [166]

For the purposes of our research, we utilize multiple logistic regression to estimate the reliability of a supplier within a LVHV supply chain. Logistic regression is a type of regression method belonging to a family of generalized linear models that evaluate the effects, include relevant interactions, and estimate response probabilities. The response and explanatory variables within the model can be categorical, discrete, binary, or continuous. Logistic regression is appropriate when the response variable describes the probability of an event. The method is used in a wide range of applications such as credit-scoring and genetics. In multiple logistic regression the response variable is based on more than one explanatory variable. Here we apply multiple logistic regression to predict the probability of success of purchases made in a LVHV supply chain, which takes the general form outlined in Equation (4.1) below. [167]

$$\text{logit} [\pi_r(\mathbf{x})] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_i x_i \quad (4.1)$$

Where: $\pi_r(\mathbf{x}) = P(Y = 1)$ at values $x = (x_1, \dots, x_p)$ of p predictors

Y is a binary response variable (4.2)

x_i is an explanatory variable (4.3)

α is the intercept parameter (4.4)

β_i is the effect of x_i on the \log odds that $Y = 1$

r is the index for the reliability model; $r = 1, \dots, 7$

i is the index for dependent variables; $i = 1, \dots, 42$

A variety of performance measures are used to evaluate the learning method being employed. Classifiers are typically evaluated by a confusion matrix, which groups the number of correctly classified positive and negative examples (true positive and true negative) and the number of incorrectly classified positive and negative examples (false positive and false negative) [166]. The general form of a confusion matrix is shown in Table 4.5.

Table 4.5: General form of confusion matrix for different outcomes of a two-class prediction.

		Predicted Class	
		Unreliable	Reliable
Actual Class	Unreliable	True Positive (TP)	False Negative (FN)
	Reliable	False Positive (FP)	True Negative (TN)

In this analysis, true positive represents the minority class (failure/unreliable) and true negative represents the majority class (success/reliable), which is a result of how the machine learning algorithm used to build the logistic regression models defines probability of success. More specifically, unreliability is defined as success. Predictive accuracy is a metric that can be derived from the confusion matrix and is defined in Equation (4.5). [168]

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (4.5)$$

Where: TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

When the data set is imbalanced a confusion matrix may not be sufficient to determine classifier performance and more robust performance measures must be used. Examples include the Receiver Operating Characteristic (ROC) curve, the Area Under the ROC Curve (AUC), precision, recall, and the F-value. The ROC curve represents the best decision boundaries for relative costs of true positive and true negative. The AUC is sometimes used because, in general, the larger the area the better the model. Additionally, the AUC can be interpreted as the probability that the classifier ranks a randomly chosen positive

instance above a randomly chosen negative one. Precision and recall are derived from the confusion matrix (see Equations (4.6) and (4.7)).

$$Precision = \frac{TP}{TP + FP} \quad (4.6)$$

$$Recall = \frac{TP}{TP + FN} \quad (4.7)$$

In general, the goal for imbalanced data sets is to improve the recall without reducing the precision. However, the two measures can be in conflict since when increasing the true positive for the minority class, the number of false positives can also be increased. In this case, the precision will reduce. The F-value (see Equation (4.8)) is another metric that is sometimes used to determine performance of a classifier. The F-value represents the tradeoffs between precision and recall and presents a single value that reflects the goodness of a classifier in the presence of rare classes. The parameter β corresponds to the relative importance of precision vs. recall and is typically set to 1. [168, 166]

$$F \text{ value} = \frac{(1 + \beta^2) \times Recall \times Precision}{\beta^2 \times Recall + Precision} \quad (4.8)$$

In addition to determining the accuracy by which the model is predicting the classes, we are also interested in better understanding the effect of each of the independent variables within the model. We use the odds ratio for each independent variable as a basis. If we define π as the probability of success, it follows that the probability of failure is $(1 - \pi)$. Success and failure are relative and depend upon how the dependent variable class is defined in the logistic regression model. In the case of this study, success is defined as unreliability and failure is defined as reliability. Odds is then defined as $\Omega = \frac{\pi}{(1 - \pi)}$ or the probability that success (unreliable event) occurs divided by the probability that failure (reliable outcome) occurs. It follows that the odds ratio (θ) is a measure of the odds of one treatment (Ω_1) in relation to another (Ω_2), $\theta = \frac{\Omega_1}{\Omega_2}$. For example, in our model, one of the independent variables is the supplier of the good or service. The odds of a particular supplier, *Supplier A*, can be described as the probability of *Supplier A* not delivering on-time over the probability of *Supplier A* delivering on time ($\Omega_A = \frac{\pi_A}{(1 - \pi_A)}$). Likewise, the odds of all other suppliers excluding *Supplier A* ($\Omega_{-A} = \frac{\pi_{-A}}{(1 - \pi_{-A})}$) can be calculated. The odds ratio for any supplier is then the quotient of the odds of that particular supplier and the odds of all other suppliers ($\theta_A = \frac{\Omega_A}{\Omega_{-A}}$). In logistic regression, the exponential function of the regression coefficient is the odds ratio ($e^{\beta_i} = \theta_i$) associated with the respective explanatory variable (x_i). [167, 169]

In order to determine the significance of the independent variables in the model, we calculate a p-value from the odds ratio based on an approach proposed by Altman et al. [?], which uses the formulae listed in Equations (4.9)-(4.12) below. By taking this approach, we test the null hypothesis ($H_o : \beta_i = 0$) to determine if the coefficient (β_i) of each dependent

variable (x_i) has a significant effect. The upper (u) and lower (l) cutoff limits for the 95% confidence interval were selected as $u = 1.2$ and $l = 0.8$ respectively.

$$Estimate = \log(\theta) \quad (4.9)$$

$$Standard\ Error = \frac{\log(u) - \log(l)}{2 \times 1.96} \quad (4.10)$$

$$z = \frac{Estimate}{Standard\ Error} \quad (4.11)$$

$$p\ value = \exp[-(0.717 \times z) - 0.416 \times z^2] \quad (4.12)$$

4.4 Numerical Results

For modeling and evaluation, we employed the use of the Waikato Environment for Knowledge Analysis (Weka) suite of machine learning software (version 3.8.2) developed by the Machine Learning Group at the University of Waikato. Weka is an open source collection of machine learning algorithms for data mining tasks and contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. [170]

In all, seven multinomial logistic regression models were built using the 42 explanatory variables described in Tables 4.1-4.3 and tested using 10-fold cross validation. Each model was subsequently evaluated using a set of standard performance metrics (Equations (4.5)-(4.8)) and explanatory variables were evaluated for significance within the model.

4.4.1 Multiple Logistic Regression Models

Tables B.1-B.7 in the Appendix summarize the results of the full multiple logistic regression training models. The coefficient (β_i), odds ratio (OR), and p-value are listed for each of the explanatory variables ($i = 1, \dots, 42$) and levels in each of the reliability models ($r = 1, \dots, 7$). An index, m ($m = 0, \dots, 442$), is introduced to represent the levels of each explanatory variable.

Weka reports a weighted average of all of the key metrics. Table 4.6 shows a summary of those results of the performance metrics for each of the seven training models after validation. All models were found to be reasonably accurate in predicting the respective unreliability metric with accuracies ranging from 0.7384 for *On-Time+Perfect Quality+Perfect Documentation* ($r = 6$) to 0.9212 for the *On-Time* model ($r = 1$). Using AUC as an overall performance metric, the *Perfect Documentation* ($r = 2$) and *On-Time+Perfect Documentation* ($r = 4$) models demonstrated the largest areas under the ROC curve with values of 0.8140 and 0.8100 respectively. *Perfect Quality* ($r = 3$) had the lowest AUC of the seven models, 0.7270.

Table 4.6: Summary of classification results.

Model (r)	Unreliability Metric / Dependent Variable	Accuracy	Precision	Recall	AUC	F-value
1	On-Time	0.9212	0.9080	0.9210	0.8010	0.9120
2	Perfect Documentation	0.7756	0.7710	0.7760	0.8140	0.7710
3	Perfect Quality	0.8972	0.8770	0.8970	0.7270	0.8820
4	On-Time + Perfect Documentation	0.7666	0.7630	0.7670	0.8100	0.7630
5	On-Time + Perfect Quality	0.8322	0.8080	0.8320	0.7520	0.8120
6	On-Time + Perfect Quality + Perfect Documentation	0.7384	0.7370	0.7380	0.7980	0.7360
7	Perfect Quality + Perfect Documentation	0.7423	0.7400	0.7420	0.7950	0.7380

4.4.2 Significance of Explanatory Variables

As noted in the previous section, the 42 explanatory variables were able to predict reasonably well the unreliability metrics chosen in this study. In this section, we explore the significance of the explanatory variables in making those predictions in more detail. As a first-level analysis, we analyzed the most positive and most negative values of β_i for each explanatory variable (i) across all seven models. In general, coefficients for those variables associated with specific suppliers ($i = 1, \dots, 17$) had the most positive and negative correlation coefficients across all levels, which indicates that suppliers who have been unreliable (or reliable) in the past are also likely to replicate their respective performance in the future. For example, one supplier ($x_{1,5}$) demonstrated a parameter value ($\beta_{1,5}$) of 25.28, which corresponds to an odds ratio ($\theta_{1,5}$) of 9.25×10^{10} for model $r = 1$ and indicates that this supplier has a 9.25×10^{10} greater odds of not delivering the products they supply on-time when compared to other suppliers.

Five variables, had coefficients equivalent to zero ($\beta_{i,m} \approx 0$) across all seven models. $\beta_{i,m} = 0$ indicates that any value of the variable associated with the coefficient results in an equal probability of outcome. Those variables included the sales volume procured from the specific supplier ($x_{17,244}$), the expected lead time of procurement ($x_{18,245}$), the date the purchase order was created ($x_{20,247}$), the quantity of items on the purchase order ($x_{21,248}$), and the value of the purchase order ($x_{35,264}$). Specific to the models developed in this

research, the aforementioned variables do not appear to have an effect on the reliability of the procurement.

In addition to analyzing the groupings of each explanatory variable (represented by i), each level within categorical explanatory variables (represented by m) was also analyzed. Figure 4.2 includes the five highest positive coefficients (β_{im}) and the five lowest negative coefficients (β_{im}) within each model. As noted above, $e^{\beta_{im}} = \theta_{im}$ where θ_{im} is the odds ratio for variable i level m . As $\beta_{im} \rightarrow +\infty$, $\theta_{im} \rightarrow +\infty$. Likewise, as $\beta_{im} \rightarrow -\infty$, $\theta_{im} \rightarrow 0$. In practice, as $\beta_{im} \rightarrow +\infty$ and $\theta_{im} \rightarrow +\infty$, the associated variable increases the probability of a successful (unreliable) outcome with respect to an unsuccessful (reliable) outcome when that particular variable increases or in the case of a categorical variable, the particular level of the variable is present. In contrast, as $\beta_{im} \rightarrow -\infty$ and $\theta_{im} \rightarrow 0$, the associated variable decreases the probability of a successful (unreliable) outcome with respect to an unsuccessful (reliable) outcome when the variable increases or the level of the variable is present. For example, in the model that estimates the probability of not delivering the particular product or service on-time ($r = 1$), the explanatory variable State (x_{16}) has 29 different levels. In other words the firm received product from 29 different states within the United States of America. For one of the states ($m = 218$) $\beta_{16,218} = +1.64$, which corresponds to $\theta_{16,218} = 5.16 \times 10^{00}$. This is analogous to saying that the odds of not delivering a product on-time from State 218 ($x_{16,218}$) is 5.16×10^{00} times greater than not delivering a product on-time when sourced from any of the other 28 states in the data set.

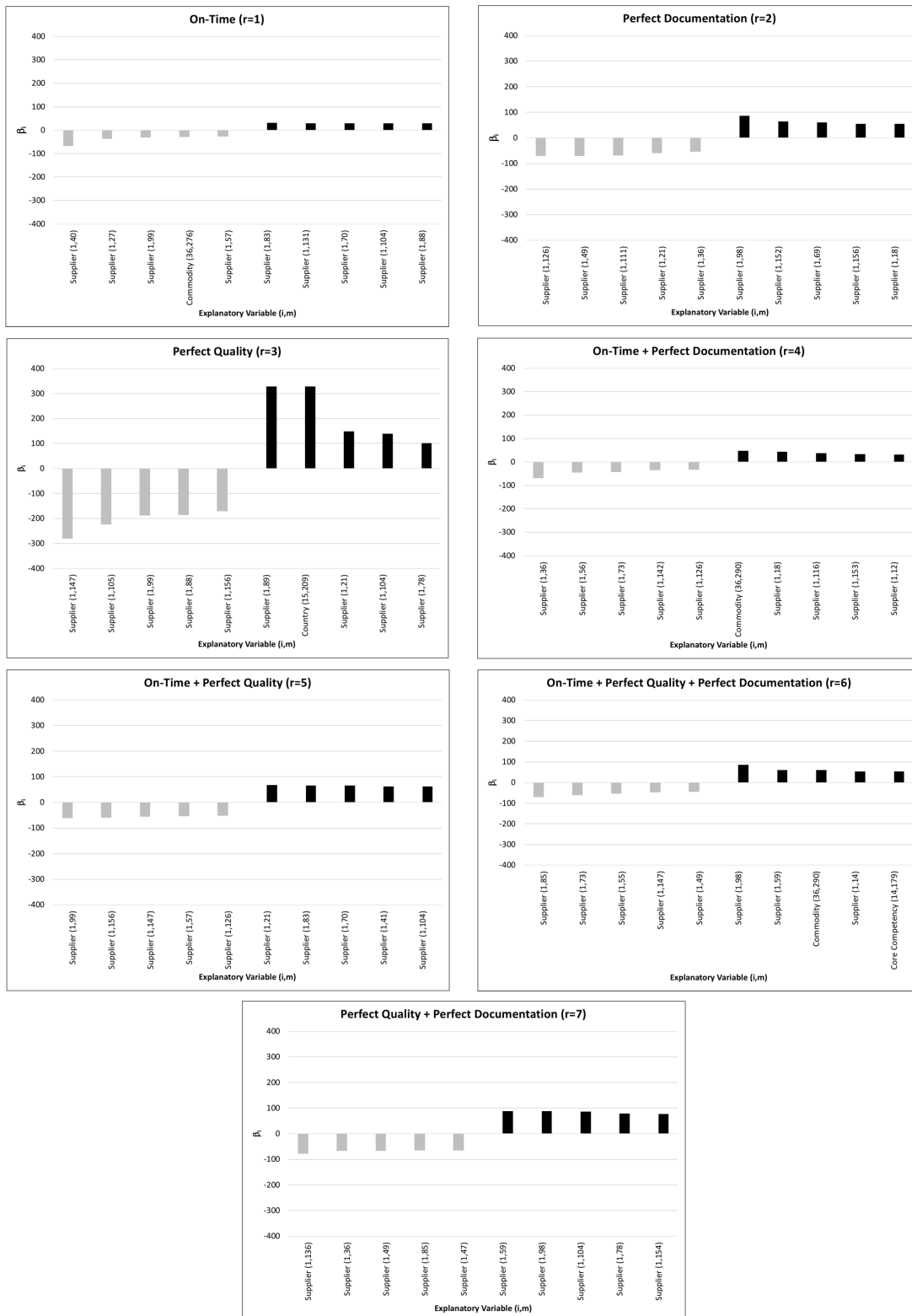


Figure 4.2: Top five and bottom five coefficient (β_{im}) values for each model.

Variables with $\theta_{im} \rightarrow -\infty$ and $\theta_{im} \rightarrow +\infty$ can both have significance within the model. We applied Equation (4.12) to derive a p-value (p_{im}) and assessed each variable's (and level's) significance at a 95% confidence level ($\alpha = 0.05$) within each model. The reader is referred to Tables B.1-B.7 in the Appendix for p-values associated with all variables within all of the full models. Of the 442 variable (i) and level (m) combinations in each model, the prediction model for *On-Time Delivery* ($r = 1$) had the highest proportion (0.9163) of significant variables and levels. The model predicting the combination of on-time delivery, perfect quality, and perfect documentation ($r = 6$) had the lowest proportion (0.8194) of significant variables and levels. Figure 4.3 summarizes the overall performance of the seven models with respect to AUC and accuracy as a function of the proportion of variables and levels. Overall, the *On-Time* ($r = 1$) prediction model seems to demonstrate the best combination of proportion of significant variables and levels and performance.

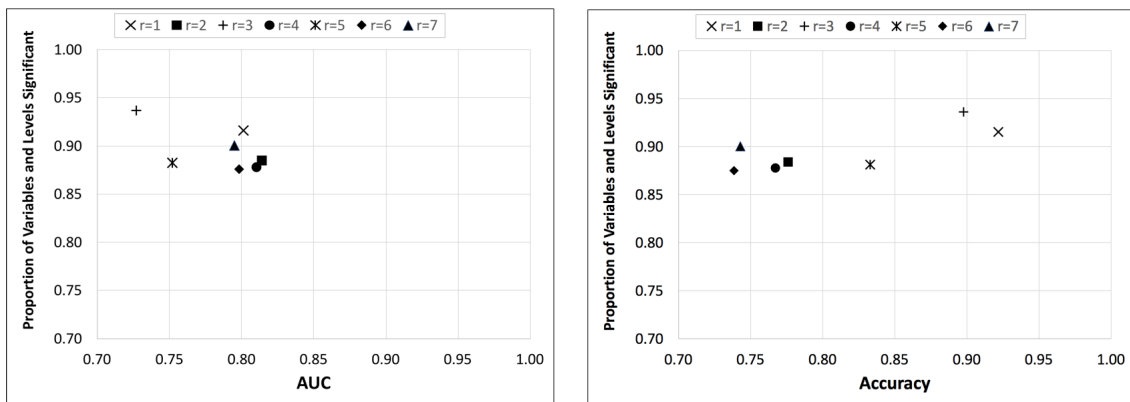


Figure 4.3: Proportion of variables and levels found to be significant as a function of AUC and accuracy.

Of all the variables and levels tested for significance, 70.6% were found to have p values < 0.05 in all seven of the models. Thus, in those instances we fail to reject the null hypothesis ($H_o : \beta_i = 0$). This proportion of significant variables and levels is heavily weighted by the number of suppliers in the study. Conversely, only 10 (2.3%) of the variables were not found to be significant across any of the seven models - *PO Line Items* ($x_{2,158}$), *POs* ($x_{3,159}$), *Rework POs* ($x_{4,160}$), *Sales* ($x_{17,244}$), *Expected Lead Time* ($x_{18,245}$), *Expected Receipt Date* ($x_{19,246}$), *Date PO Line Created* ($x_{20,247}$), *PO Line Quantity* ($x_{21,248}$), *Quality Requirements* ($x_{33,262}$), and *Value* ($x_{35,264}$). Three variables - *Level 2 Qualifications* ($x_{6,162}$), *Qualifications* ($x_{13,169}$), and *Qualification Requirements* ($x_{32,261}$) - were only found to be significant (p value < 0.05) in the *On-Time* ($r = 1$) model. Other variables were found to be significant in some models, but not all models. Variables with several levels were found to have some levels that were significant while other levels were not. Figures 4.4 - 4.7 summarize the significant variables (p values < 0.05) in each of the seven models, which are noted using the symbol β_i .

Description	i	m	On-Time	Perfect Documentation	Perfect Quality	On-Time + Perfect Documentation	On-Time + Perfect Quality	On-Time + Perfect Quality + Perfect Documentation	Perfect Quality + Perfect Documentation
State	16	225	●	●	●	●	●	●	●
State	16	226	●	●	●	●	●	●	●
State	16	227	●	●	●	●	●	●	●
State	16	228	●	●	●	●	●	●	●
State	16	229	●	●	●	●	●	●	●
State	16	230	●	●	●	●	●	●	●
State	16	231	●	●	●	●	●	●	●
State	16	232	●	●	●	●	●	●	●
State	16	233	●	●	●	●	●	●	●
State	16	234	●	●	●	●	●	●	●
State	16	235	●	●	●	●	●	●	●
State	16	236	●	●	●	●	●	●	●
State	16	237	●	●	●	●	●	●	●
State	16	238	●	●	●	●	●	●	●
State	16	239	●	●	●	●	●	●	●
State	16	240	●	●	●	●	●	●	●
State	16	241	●	●	●	●	●	●	●
State	16	242	●	●	●	●	●	●	●
State	16	243	●	●	●	●	●	●	●
Sales	17	244							
Expected Lead Time	18	245							
Expected Receipt Date	19	246							
Date PO Line Created	20	247							
PO Line Quantity	21	248							
Multiple Receipts per Line	22	249	●	●	●	●	●	●	●
Multiple Receipts per Line	22	250	●	●	●	●	●	●	●
Multiple Receipts per Line	22	251	●	●	●	●	●	●	●
Rework	23	252	●	●	●	●	●	●	●
Quarter and Year of Receipt	24	253							
Month and Year of Receipt	25	254	●	●	●	●	●	●	●
Level 1 Qualification Requirements	26	255	●	●	●	●	●	●	●
Level 2 Qualification Requirements	27	256	●	●	●	●	●	●	●
Level 3 Qualification Requirements	28	257	●	●	●	●	●	●	●
Level 4 Qualification Requirements	29	258	●	●	●	●	●	●	●
Highest Qualification Requirement	30	259	●	●	●	●	●	●	●
Lowest Qualification Requirement	31	260	●	●	●	●	●	●	●
Qualification Requirements	32	261			●				
Quality Requirements	33	262							
Program Family or Generic	34	263	●		●				
Value	35	264							
Commodity	36	265	●	●	●	●	●	●	●
Commodity	36	266	●	●	●	●	●	●	●
Commodity	36	267	●	●	●	●	●	●	●
Commodity	36	268	●	●	●	●	●	●	●
Commodity	36	269	●	●	●	●	●	●	●
Commodity	36	270	●	●	●	●	●	●	●
Commodity	36	271	●	●	●	●	●	●	●
Commodity	36	272	●	●	●	●	●	●	●
Commodity	36	273	●	●	●	●	●	●	●
Commodity	36	274	●	●	●	●	●	●	●
Commodity	36	275	●	●	●	●	●	●	●
Commodity	36	276	●	●	●	●	●	●	●
Commodity	36	277	●	●	●	●	●	●	●
Commodity	36	278	●	●	●	●	●	●	●
Commodity	36	279	●	●	●	●	●	●	●
Commodity	36	280	●	●	●	●	●	●	●

Description	i	m	On-Time	Perfect Documentation	Perfect Quality	On-Time + Perfect Documentation	On-Time + Perfect Quality	On-Time + Perfect Quality + Perfect Documentation	Perfect Quality + Perfect Documentation
Commodity	36	281	●	●	●	●	●	●	●
Commodity	36	282	●	●	●	●	●	●	●
Commodity	36	283	●	●	●	●	●	●	●
Commodity	36	284	●	●	●	●	●	●	●
Commodity	36	285	●	●	●	●	●	●	●
Commodity	36	286	●	●	●	●	●	●	●
Commodity	36	287	●	●	●	●	●	●	●
Commodity	36	288	●	●	●	●	●	●	●
Commodity	36	289	●	●	●	●	●	●	●
Commodity	36	290	●	●	●	●	●	●	●
Commodity	36	291	●	●	●	●	●	●	●
Commodity	36	292	●	●	●	●	●	●	●
Commodity	36	293	●	●	●	●	●	●	●
Commodity	36	294	●	●	●	●	●	●	●
Commodity	36	295	●	●	●	●	●	●	●
Commodity	36	296	●	●	●	●	●	●	●
Commodity	36	297	●	●	●	●	●	●	●
Commodity	36	298	●	●	●	●	●	●	●
Commodity	36	299	●	●	●	●	●	●	●
Commodity	36	300	●	●	●	●	●	●	●
Commodity	36	301	●	●	●	●	●	●	●
Commodity	36	302	●	●	●	●	●	●	●
Commodity	36	303	●	●	●	●	●	●	●
Commodity	36	304	●	●	●	●	●	●	●
Item/Service Identifier	37	305	●	●	●	●	●	●	●
Item/Service Identifier	37	306	●	●	●	●	●	●	●
Item/Service Identifier	37	307	●	●	●	●	●	●	●
Item/Service Identifier	37	308	●	●	●	●	●	●	●
Item/Service Identifier	37	309	●	●	●	●	●	●	●
Item/Service Identifier	37	310	●	●	●	●	●	●	●
Item/Service Identifier	37	311	●	●	●	●	●	●	●
Item/Service Identifier	37	312	●	●	●	●	●	●	●
Item/Service Identifier	37	313	●	●	●	●	●	●	●
Item/Service Identifier	37	314	●	●	●	●	●	●	●
Item Family	38	315	●	●	●	●	●	●	●
Item Family	38	316	●	●	●	●	●	●	●
Item Family	38	317	●	●	●	●	●	●	●
Item Family	38	318	●	●	●	●	●	●	●
Item Family	38	319	●	●	●	●	●	●	●
Item Family	38	320	●	●	●	●	●	●	●
Item Family	38	321	●	●	●	●	●	●	●
Item Family	38	322	●	●	●	●	●	●	●
Item Family	38	323	●	●	●	●	●	●	●
Item Family	38	324	●	●	●	●	●	●	●
Item Family	38	325	●	●	●	●	●	●	●
Item Family	38	326	●	●	●	●	●	●	●
Item Family	38	327	●	●	●	●	●	●	●
Item Family	38	328	●	●	●	●	●	●	●
Item Family	38	329	●	●	●	●	●	●	●
Item Family	38	330	●	●	●	●	●	●	●
Item Family	38	331	●	●	●	●	●	●	●
Item Family	38	332	●	●	●	●	●	●	●
Item Family	38	333	●	●	●	●	●	●	●
Item Family	38	334	●	●	●	●	●	●	●
Item Family	38	335	●	●	●	●	●	●	●
Item Family	38	336	●	●	●	●	●	●	●

●: p < 0.05

Figure 4.6: Summary of significant variables (3 of 4).

Of particular interest in this study are the results that indicate which variables do not have a significant impact on the reliability of a procurement regardless of the reliability metric used as the dependent variable. The 10 variables (noted above) fall into two of the three explanatory variable groups - related to the supplier and related to the purchase order. More specifically, the volume of work awarded to the supplier ($x_{2,158}$, $x_{3,159}$, $x_{17,244}$) or the amount of rework ($x_{4,160}$) completed by the supplier on the purchase order over a four year time span was not found to be a significant factor in a supplier's reliability. This is somewhat contradictory to common logic, which would suggest that the more a firm works with a supplier, the more reliable they become.

Of the six variables related to the purchase order that were not found to be significant contributors to reliability, three ($x_{18,245}$, $x_{19,246}$, $x_{20,247}$) correspond to the timing of the procurement and more specifically, the expected lead time for the procurement, the time of year the procurement is expected, and when the purchase order was created. Although interesting, additional investigation is required if these results indicate that seasonality with respect to these variables does not exist.

The volume on the purchase order both in terms of quantity ($x_{21,248}$) and value ($x_{35,264}$) were not found to be significant contributors in any of the reliability models. Like the historical volume awarded to the supplier, the volume placed on a specific purchase order does not appear to contribute to the reliability of a procurement. Lastly, the number of qualification requirements ($x_{32,261}$) indicated on the purchase order was also found not be significant, which suggests that neither more or less requirements improve or reduce the reliability of a procurement.

4.5 Conclusions

In this chapter, we developed seven reliability prediction models using a combination of multinomial logistic regression and 10-fold cross validation based on actual data collected within a LVHV supply chain. The dependent variables within each model were based on the APICS SCOR[®] Model definition for reliability. In the logistic regression model, success was defined as unreliability. More specifically, the seven models were constructed to predict the probability that a purchase is not delivered *On-Time*, without *Perfect Documentation*, without *Perfect Quality*, and combinations thereof. The models were based on a total of 42 independent variables. Each variable and level within each model was tested for statistical significance (95% confidence level).

Supplier related variables describing the volume of work awarded to the supplier (purchase order line items, purchase orders, reworked purchase orders, and total sales) throughout the year were not found to be significant contributors to reliability. Similarly, variables associated with the purchase order itself such as the expected lead time, the time of year that the receipt was expected, when the purchase order was created, the number of items on the purchase order line, the total number of quality requirements, or overall value of the purchase order were found to not have any significance with respect to reliability. Further, in the majority of cases the supplier chosen for the procurement, the core competency of the supplier, and the supplier's location were found to be significant contributors. All variables associated with the item itself demonstrated significance in at least two of the seven models.

In addition to statistical significance of individual explanatory variables and categories within explanatory variables, metrics for each model were analyzed to assess the ability for the explanatory variables to predict reliability. All classification metrics for all models indicated a relatively high level of accuracy (0.7384-0.9212), precision (0.7370-0.9080), recall (0.7380-0.9210), AUC (0.7270-0.8140), and F-measure (0.7360-0.9120).

The application of the models described within this chapter has practical significance in predicting the reliability/unreliability of a purchase within a LVHV supply chain. The data used to build the models described herein is readily available in most firms that have ERP systems. For those firms that do not employ systems to readily collect the data described, implementing sufficient data collection streams would not be difficult. Supply chain professionals can use the resulting models to assess and compare suppliers, items to be purchased, or purchase order characteristics across one or more than one of seven measures of reliability. In addition, where sole or single sources of supply are required, the firm making the purchase will have a better understanding of the reliability and can decide to take appropriate measures to mitigate the associated risks. The features of this approach are an improvement over methods currently employed in the industry. The models presented within this chapter are specific to the data sets upon which they were built. However, the methods to build such models as those described have the potential of being transferrable to other firms' data when combined with specific knowledge of the business.

Several areas of future work are recommended. The data set used to develop these models was contained to one year. Using the same methods described here to construct models on other supply chains would be interesting as well as a useful extension. Like-

wise, including additional explanatory variables, the interaction of explanatory variables, as well as exploring the use of other machine learning classification algorithms in comparison to the multinomial logistic regression methodology described here would serve to further substantiate our approach. One example of a variable that was not available at the time of this study relates to the single or sole source position of the supplier in the supply chain. Understanding the impact of these types of suppliers on the reliability of procurements would be beneficial in the supplier selection process as well as during risk mitigation planning. Lastly, we plan to deploy the model in a real-world application in order to further validate the prediction capabilities of the models.

CHAPTER 5

CONCLUSIONS

5.1 Summary

The focus of this research was to develop foundational methods for practitioners in a LVHV supply chain to predict, evaluate, and mitigate risks within the supply chain in advance of those risks being realized. Although developed using data and case studies from a LVHV supply chain, the methodology has potential application in other types of supply chains. The ability to organize a supply chain schematically, identify potential risks, assess the overall reliability of the supply chain, and predict the reliability of a procurement are all activities that are important to a firm's success. The inability to perform these tasks with some degree of success can have catastrophic consequences to a firm's financial stability and to an entire industry. The supply chains that are used to construct nuclear power plants are one example of an industry that has suffered such consequences.

The methods discussed in this dissertation outline an approach using fault tree analysis to organize a supply chain schematically from the bill of materials of the product being sourced. Next, we leveraged the structure of the fault tree in combination with Boolean algebra to evaluate the overall reliability of the supply chain. Subsequently, we developed optimization models to identify potential risks as well as mitigation activities to maximize the supply chain system reliability under budgetary constraints. Lastly, we defined reliabil-

ity using standard industry metrics and developed a multinomial logistic regression model to predict the reliability/unreliability of a procurement using data from a LVHV firm. Contributions to the literature were made in each of the areas discussed.

In the sections that follow, we draw conclusions more specifically within each area of the research and discuss recommendations for future work.

5.2 Model Supply Chain Risk

In this dissertation, we introduced a new application for fault tree analysis, which served as a foundational element of our research. The use of a fault tree to represent a supply chain enabled the use of the techniques associated with fault tree analysis to evaluate the supply chain as a system. Further, by using a product's bill of materials as the basis for constructing the fault tree, the method provides the flexibility to evaluate the supply chain at various tiers and from a variety of perspectives. Case studies using examples of products sourced in a LVHV industry were presented to demonstrate the practical application of such an approach.

After constructing the fault tree, we calculated the overall system unreliability of the supply chain. Next, four scenarios that practitioners face were proposed to demonstrate the usefulness of the concept as an evaluation tool when making procurement decisions. The scenarios included adding a second redundant supplier, improving the existing supplier, replacing the existing supplier with an improved supplier, and adding a second improved supplier. A cost model was proposed and applied to each of the four scenarios being evaluated. Subsequently, the system unreliability was re-calculated for each of the

four scenarios. The tradeoff between the mitigation cost and unreliability improvement were evaluated for each of the scenarios in comparison to the baseline scenario where no modifications to the supply chain were made.

The results of the study indicated that introducing a redundant supplier with improved performance provided the greatest reduction in system unreliability at a slightly lower total cost than adding an equivalently unreliable supplier. Although specific to the supply chain and decisions posed for each scenario, the results demonstrated the approach as a tool for supply chain professionals to evaluate seemingly indistinguishable decision outcomes in an objective and quantitative way. Furthermore, the method provides an opportunity to evaluate the potential decision outcomes and impact on the supply chain system prior to carrying out a procurement decision. In the absence of the tools presented, decisions are left to a high degree of subjectivity and made within silos without knowledge of other related decisions. The methodology presented provides a significant improvement to the current manner in which procurement decisions are made in LVHV supply chains. Further, greater visibility is given to the potential costs of decisions and higher risk areas within a supply chain system. In conclusion, the research presented here demonstrates that a complex supply chain can be organized as a system using a fault tree architecture and subsequently analyzed to assess risk.

5.3 Mitigate Supply Chain Risk

In the second of the three arms of the research presented in this dissertation, we built upon the concept of representing a supply chain as a fault tree based on a product's bill

of materials and applied mixed integer programs to optimize the overall reliability of the system by selecting risk mitigating actions with consideration for budgetary constraints. More specifically, we developed two models and applied those models to LVHV firms that participate in two separate tiers of the nuclear power plant construction supply chain to demonstrate the robustness of the approach. The first firm studied is responsible for delivering the pressurized water reactor to the nuclear power plant. The second supply chain studied was a lower tier supplier providing a thrust bearing; a major component in the steam turbine, which is part of the pressurized water reactor.

The first modeling approach presented, referred to as the PMM, focused on selecting risk mitigating actions that set the reliability of the minimal cut set within the fault tree equal to 100% reliability. Like before, suppliers are represented as basic events in the model and sets of suppliers comprise minimal cut sets. Although directionally helpful to apply risk mitigating actions on sets of suppliers in the supply chain, the PMM does not select the specific risk mitigation action to apply to a specific supplier. All risk mitigating actions were given a standard cost of \$12,209, which represented the cost associated with improving a supplier's reliability by 15% over their current performance.

Extending the PMM, we developed an IMM. Although similar to the approach developed for the PMM, the IMM delivers additional information regarding the specific mitigation actions to take on specific suppliers. We selected four mitigation options with different costs and associated reliability improvements to demonstrate the approach. In order to more effectively apply a mixed integer optimization program to the fault tree architecture, we converted the fault tree into a binary decision diagram using the component connection

method. Doing so reduced the mathematical complexities associated with optimizing directly on the fault tree and further enabled the model to select specific suppliers to mitigate within the supply chain.

Both mitigation models were applied to two supply chains, run at a range of risk mitigation budgets, and results compared to one another. The results demonstrated the value and practical nature of the approach to supply chain professionals tasked with making mitigation decisions across two sizes and scopes of LVHV supply chains. Further, this research illustrated methods to select activities that should be undertaken to mitigate risk within the supply chain and simultaneously minimize risk while at the same time achieving budgetary goals.

5.4 Quantify Supplier Risk

The objective of the third topic outlined in this dissertation was to develop a mathematical model to predict the reliability of a procurement in a LVHV supply chain. The explanatory variables in the model were selected based on the experience of supply chain professionals. Additionally, to prove the practical worthiness of the model, the underlying data describing each of the explanatory variables selected for the model had to be available via a firm's ERP system. Using a set of 42 explanatory variables, we developed seven multinomial logistic regression models. Each model described supply chain reliability in terms of on-time delivery, first time hardware quality, first time documentation quality, and the combinations thereof.

Logistic regression was chosen as the modeling method because the response variable describes the probability of an event. Ten-fold cross validation was applied to assess the performance of each of the seven models. In general, each model performed well (> 0.7200) across all of the performance metrics selected. In addition to analyzing the magnitudes of the coefficients of each variable, we tested the odds ratio for each of the explanatory variables and levels for statistical significance.

Overall, the results indicated that variables associated with the supplier, the geographic location of the supplier, and the supplier's core competencies were significant with respect to reliably supplying product to the firm. However, in general terms neither the volume of the product procured nor the timing of the procurement were found to be significant. These conclusions provide insight for the supply chain professional to focus more effort on the supplier and the suppliers' attributes to manage the associated risks; whereas, less priority should be given to adjusting the quantity procured, managing the structure of the purchase order, or controlling the timing of the procurement. Further, the results correspond well with the observations made by Schlissel et al. [4] regarding the erosion of qualified and capable suppliers within the nuclear industry and further substantiate the need to invest time in the supplier selection process to ensure that suppliers are competent to complete the work requested of them.

In conclusion, the logistic regression model developed as part of this research demonstrates a practical method to predict the reliability of a procurement in a LVHV supply chain. In doing so, we were also able to provide insight as to the significant factors that affect reliability. Both of these results have practical significance in supply chain risk man-

agement, improve a firm's ability to more quantitatively understand the supply chain risks faced, and subsequently minimize the effects of those risks.

5.5 Research Limitations and Future Work

The research contained in this dissertation was limited to LVHV supply chains. Extending and testing these concepts across different supply chains in different industries would be both useful and interesting.

In addition, although building off one another each of the three areas of research presented were done independently. Developing a software instrument that integrates the three areas together would have significant practical application. Doing so would also improve the applicability across supply chain practitioners of varying levels of computational experience. More specifically, the activities associated with constructing a fault tree from a firm's bill of materials, converting the fault tree into a binary decision diagram, and applying the proposed optimization models is somewhat tedious. Automating and integrating these processes could prove useful as would tying the data streams used into a firm's ERP system.

The cost model presented as part of "Modeling Supply Chain Risk" was based on empirical data. However, improving it and extending it into the areas described within "Mitigate Supply Chain Risk" would be useful. In addition, studying the cost sensitivity around budgets and the resulting risk mitigating decisions could have practical importance for supply chain budget managers. More specifically, expanding the cost modeling capability to include better insights into the marginal utility between the risk mitigation budget and

the resulting supply chain portfolio reliability could be useful in setting budgets, planning resources, and selecting suppliers.

In both the “Modeling Supply Chain Risk” and “Mitigating Supply Chain Risk” areas presented, the supplier is assumed to be known by the firm. In practice, this is not always the case. For example, the data used in this research is not available for new suppliers that the firm is considering. On one hand, this further validates the efficacy and need for the model presented within the “Quantify Supplier Risk” research area. In contrast, if the supplier is unknown completely, the methods presented are difficult to implement. As a result, developing a method to predict a supplier’s reliability based on a set of attributes would be helpful. The work completed within this dissertation can serve as a basis to explore this area further.

The approach presented to model the supply chain system as a fault tree assumes independence and a static state. However, in reality supply chains are neither independent nor static. We relaxed the independence assumption to some extent by integrating suppliers and procurements with similar characteristics through the logistic regression model and underlying data sets. Exploring the dependence of suppliers, events, decisions, and consequences, across the supply chain in more detail is a worthy effort. The application of dynamic fault tree analysis, stochastic models, and other available methods is recommended. Similarly, throughout this research we assumed that events were immediately repairable and did not investigate the effects that downtime or unrepairable events may have on the supply chain.

The methods described within this research effectively utilize probability as a basis for reliability. However, like downtime, we did not analyze the supply chains being studied in terms of the severities or the consequences associated with the definition of risk. Further, we did not extend our approaches into the financial impacts that decisions or risks may have on the firm's overall financial performance. Paths to assess various metrics of risk using the methods described in this dissertation are recommended as future research and would have practical significance.

The logistic regression model presented serves as a foundation for further research. First, it would be interesting to develop models for different supply chains and using different machine learning classification methods to compare results and test the overarching hypothesis that LVHV supply chains are in-fact different than other supply chain constructs. Furthermore, we did not include interaction variables within our model. This may also prove as a useful extension as well as the inclusion of additional explanatory variables. The variables included in the model were restricted to those collected by the firm. One example of a variable that may have practical significance is related to a supplier's sole or single source position within a firm's supply chain.

Lastly, we recommend implementing the concepts contained within this dissertation either in part or in full within a LVHV firm to further validate the concepts proposed. When implemented decisions made should be logged and compared with the actual outcomes and costs incurred. For example, a supply chain professional may determine that adding a redundant supplier will reduce the overall risk within the portfolio to an acceptable level when developing a fault tree to represent the bill of material of the product being sourced.

After implementing the decision, the results should be monitored to determine if the overall reduction in portfolio risk was achieved. If the results predicted by the model were not realized, causes should be identified, and modifications should be made to tune the accuracy of the model. Similar analyses could be performed to determine the accuracy of the predicted results with respect to mitigating risks and allocating resources when a firm implements the optimization models presented within this research as part of their decision toolkit.

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APPENDIX A
SUMMARY OF NOTATION

Table A.1: Summary of notation used in Chapter 2.

Notation	Description
$F(t)$	probability that the system experiences at least one failure during a specified time period
t	time period; 52 weeks
$R(t)$	probability that the supplier makes all of its deliveries on time within the time interval
$f_{ij}(t)$	probability that the supplier has failed to deliver their respective service on time within the interval $[0, t]$
i	supplier
j	service
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
n	total number of basic services within supply chain
m	total number of suppliers within supply chain
g_k^{OR}	the gate unreliability of OR gate k
g_k^{AND}	the gate unreliability of AND gate k
q	the total number of gates within the fault tree
k	fault tree gate index
F_S	Fault tree system unreliability
$t_{ij}^{improve}$	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	≈ 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
$c_{ij}^{onboard}$	cost of adding new supplier or replacing an existing with an improved supplier
$c_{ij}^{improve}$	cost of improving an existing supplier
$c_{ij}^{oversight}$	cost of providing oversight to a supplier to maintain performance

Table A.2: Summary of notation used in Chapter 3.

Notation	Description
\mathbb{U}_i	the probability that cut set i occurs; unreliability of cut set i
i	minimal cut set index
I	set of all minimal cut sets
x_i	binomial decision variable; $x_i = 1$ if minimal cut set i is mitigated and 0 otherwise
y_j	binomial decision variable; $y_j = 1$ if supplier j is mitigated and 0 otherwise
j	supplier index
J	set of all suppliers
J_i	set of suppliers that are members of cut set i
b	total mitigation budget of the firm
c_j	cost of mitigating supplier j
c_{jk}	cost of mitigating supplier j with mitigation activity k
$\mathbb{P}_{j,\ell(j,\omega)}$	the probability of supplier j in path ω with state ℓ
ω	terminal 1 node path
ℓ	state; $\ell = 0$ if success state and $\ell = 1$ if failed state
$\mathbb{P}_{j,\omega}$	simplified notation for $\mathbb{P}_{j,\ell(j,\omega)}$
Ω	terminal 1 node paths
J_ω	set of suppliers contained in path ω
k	mitigation activity performed on a supplier
$\mathbb{P}_{j,\omega,k}$	the probability that supplier j along path ω given mitigation activity k was performed on supplier j
y_{jk}	binary decision variable; $y_{jk} = 1$ if mitigation activity k performed on supplier j and 0 otherwise
w_{rk}^ω	the partial probability associated with each path (ω)
r	the order of the supplier within path (ω)
$ J_\omega $	all suppliers with path (ω) beginning with the second ($r = 2$) supplier in the path
k_j^*	mitigation selected for supplier j in the optimal solution
u_j	unreliability of supplier j
\mathcal{U}_S	unreliability of the system being studied
\mathcal{U}_S^{REA}	unreliability of the system being studied; calculated using the rare event approximation
\mathcal{R}_S	reliability of the system being studied
\mathcal{R}_S^{PMM}	reliability of system being studied; calculated using the perfect mitigation model
\mathcal{R}_S^{IMM}	reliability of system being studied; calculated using the imperfect mitigation model
s	metric used to compare the perfect and imperfect mitigation model differences of the system being studied

Table A.3: Summary of notation used in Chapter 4.

Notation	Description
r	index for the reliability model
n	number of purchase orders and line items
i	index for explanatory/dependent variables
p	number of predictors
$\pi_r(\mathbf{x})$	probability that $Y = 1$
Y	binary response variable
x_i	explanatory variable
α	intercept parameter
β_i	the effect of x_i on the log odds that $Y = 1$
π	probability of success
	a parameter corresponding to the relative importance of precision vs. recall
Ω	odds
θ	odds ratio
u	upper cutoff limit for the 95% confidence interval
l	lower cutoff limit for the 95% confidence interval
z	z-score; indicates how many standard deviations an element is from the mean
m	index representing the levels of each explanatory variable

APPENDIX B

EXTRA MATERIAL FOR CHAPTER 4

Table B.1: Summary results of full model (1 of 7).

Description	i	m	r1			r2			r3			r4			r5			r6			r7					
			β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value			
Intercept	0	1	413.95	1.25	<0.0001	-612.21	0.07	<0.0001	618.11	0.39	<0.0001	-562.09	0.46	<0.0001	654.98	0.63	<0.0001	-523.34	0.53	<0.0001	-562.09	0.46	<0.0001	654.98	0.63	<0.0001
Supplier	1	2	4.65	1.04E-02	<0.0001	-1.11	3.26E-01	<0.0001	12.45	5.72E-01	<0.0001	0.56	5.91E-06	<0.0001	8.67	3.86E-00	<0.0001	-7.37	1.95E-01	<0.0001	0.56	5.91E-06	<0.0001	8.67	3.86E-00	<0.0001
Supplier	1	3	4.65	1.04E-02	<0.0001	-1.11	3.26E-01	<0.0001	12.45	5.72E-01	<0.0001	0.56	5.91E-06	<0.0001	8.67	3.86E-00	<0.0001	-7.37	1.95E-01	<0.0001	0.56	5.91E-06	<0.0001	8.67	3.86E-00	<0.0001
Supplier	1	4	-0.36	6.97E-01	0.0132	-0.19	8.26E-01	0.1213	-0.76	4.66E-01	0.0002	-0.61	5.41E-01	0.0012	-0.93	3.94E-01	<0.0001	-0.36	6.97E-01	<0.0001	-0.61	5.41E-01	0.0013	-0.93	3.94E-01	<0.0001
Supplier	1	5	2.05	1.49E-01	<0.0001	-1.12	3.19E-01	<0.0001	3.13	1.07E-01	<0.0001	-1.13	3.19E-01	<0.0001	4.11	1.56E-00	<0.0001	-1.12	3.19E-01	<0.0001	-1.13	3.19E-01	<0.0001	4.11	1.56E-00	<0.0001
Supplier	1	6	1.33	3.78E-00	<0.0001	-1.62	2.47E-01	<0.0001	2.93	1.87E-01	<0.0001	-1.45	2.84E-01	<0.0001	0.81	1.59E-00	<0.0001	-1.75	1.71E-01	<0.0001	-1.45	2.84E-01	<0.0001	0.81	1.59E-00	<0.0001
Supplier	1	7	-0.79	4.53E-01	0.0002	0.29	1.33E-01	0.0107	-0.41	6.61E-01	0.0416	-0.27	1.33E-01	0.0484	-0.14	7.71E-01	<0.0001	0.43	1.73E-00	<0.0001	-0.27	1.33E-01	0.0567	0.27	1.31E-00	0.0499
Supplier	1	8	-5.11	6.10E-03	<0.0001	-2.29	1.01E-01	<0.0001	2.28	1.94E-00	<0.0001	-1.32	2.68E-01	<0.0001	2.02	2.75E-00	<0.0001	-6.32	1.86E-03	<0.0001	-1.32	2.68E-01	<0.0001	2.02	2.75E-00	<0.0001
Supplier	1	9	5.78	2.31E-02	<0.0001	-4.89	3.49E-01	<0.0001	1.87	1.02E-01	<0.0001	-1.33	1.97E-02	<0.0001	3.99	6.09E-00	<0.0001	-9.80	1.06E-04	<0.0001	-1.33	1.97E-02	<0.0001	3.99	6.09E-00	<0.0001
Supplier	1	10	-0.78	2.31E-02	<0.0001	-4.89	3.49E-01	<0.0001	1.87	1.02E-01	<0.0001	-1.33	1.97E-02	<0.0001	3.99	6.09E-00	<0.0001	-9.80	1.06E-04	<0.0001	-1.33	1.97E-02	<0.0001	3.99	6.09E-00	<0.0001
Supplier	1	11	0.63	1.87E-00	<0.0010	-5.69	4.06E-01	<0.0001	-15.54	0.00E+00	<0.0001	-4.75	8.70E-03	<0.0001	2.87	1.77E-01	<0.0001	-9.47	1.00E-04	<0.0001	-4.75	8.70E-03	<0.0001	2.87	1.77E-01	<0.0001
Supplier	1	12	24.20	3.23E-10	<0.0001	38.43	4.06E-16	<0.0001	-15.83	0.00E+00	<0.0001	31.84	6.71E-13	<0.0001	36.54	7.99E-15	<0.0001	19.52	3.01E-08	<0.0001	-15.83	0.00E+00	<0.0001	31.84	6.71E-13	<0.0001
Supplier	1	13	17.23	4.58E-07	<0.0001	26.71	1.84E-05	<0.0001	-10.27	2.09E-01	<0.0001	27.25	6.89E-11	<0.0001	38.67	8.48E-10	<0.0001	33.80	2.33E-02	<0.0001	-10.27	2.09E-01	<0.0001	27.25	6.89E-11	<0.0001
Supplier	1	14	17.62	4.58E-07	<0.0001	3.91	2.08E-02	<0.0001	-84.69	0.00E+00	<0.0001	-0.80	4.48E-01	<0.0001	2.44	1.14E-01	<0.0001	-4.27	1.39E-02	<0.0001	-0.80	4.48E-01	<0.0001	2.44	1.14E-01	<0.0001
Supplier	1	15	5.78	3.24E-02	<0.0001	-9.46	1.09E-04	<0.0001	5.59	2.67E-02	<0.0001	-9.13	1.00E-04	<0.0001	1.56	4.77E-00	<0.0001	-5.42	4.46E-03	<0.0001	-9.13	1.00E-04	<0.0001	1.56	4.77E-00	<0.0001
Supplier	1	16	2.61	3.36E-01	<0.0001	-3.91	2.08E-02	<0.0001	3.91	2.08E-02	<0.0001	-3.91	2.08E-02	<0.0001	2.44	1.14E-01	<0.0001	-5.42	4.46E-03	<0.0001	-3.91	2.08E-02	<0.0001	2.44	1.14E-01	<0.0001
Supplier	1	17	1.01	1.01E-01	<0.0001	-1.01	1.01E-01	<0.0001	1.01	1.01E-01	<0.0001	-1.01	1.01E-01	<0.0001	1.01	1.01E-01	<0.0001	-1.01	1.01E-01	<0.0001	-1.01	1.01E-01	<0.0001	1.01	1.01E-01	<0.0001
Supplier	1	18	4.73	1.20E-03	<0.0001	55.36	1.13E-21	<0.0001	-80.54	0.00E+00	<0.0001	-43.38	6.89E-18	<0.0001	33.51	8.09E-00	<0.0001	29.56	6.06E-11	<0.0001	-43.38	6.89E-18	<0.0001	33.51	8.09E-00	<0.0001
Supplier	1	19	1.15	3.15E-00	<0.0001	-0.46	6.13E-01	<0.0001	4.59	9.90E-01	<0.0001	-0.35	7.04E-01	<0.0001	1.17	3.21E-00	<0.0001	-0.92	3.97E-01	<0.0001	-0.35	7.04E-01	<0.0001	1.17	3.21E-00	<0.0001
Supplier	1	20	-5.13	5.90E-03	<0.0001	6.59	7.29E-02	<0.0001	-14.38	1.75E-06	<0.0001	-7.13	1.28E-03	<0.0001	16.56	1.56E-07	<0.0001	-0.93	3.99E-01	<0.0001	-7.13	1.28E-03	<0.0001	16.56	1.56E-07	<0.0001
Supplier	1	21	7.77	4.00E-04	<0.0001	-1.04	3.53E-01	<0.0001	0.73	2.08E-00	<0.0001	-0.82	4.42E-01	<0.0001	0.44	1.55E-00	<0.0001	-0.96	3.83E-01	<0.0001	-0.82	4.42E-01	<0.0001	0.44	1.55E-00	<0.0001
Supplier	1	22	9.95	2.59E-05	<0.0001	-4.32	7.48E-01	<0.0001	11.41	0.00E+00	<0.0001	-9.58	2.81E-01	<0.0001	32.32	8.09E-00	<0.0001	-2.57	7.64E-01	<0.0001	-9.58	2.81E-01	<0.0001	32.32	8.09E-00	<0.0001
Supplier	1	23	1.11	3.02E-00	<0.0001	-1.04	3.53E-01	<0.0001	0.73	2.08E-00	<0.0001	-0.82	4.42E-01	<0.0001	0.44	1.55E-00	<0.0001	-0.96	3.83E-01	<0.0001	-0.82	4.42E-01	<0.0001	0.44	1.55E-00	<0.0001
Supplier	1	24	-7.77	4.00E-04	<0.0001	48.85	1.64E-21	<0.0001	-15.63	0.00E+00	<0.0001	10.23	2.77E-04	<0.0001	-31.65	0.00E+00	<0.0001	13.41	6.67E-05	<0.0001	-15.63	0.00E+00	<0.0001	10.23	2.77E-04	<0.0001
Supplier	1	25	4.73	1.20E-03	<0.0001	-1.01	1.01E-01	<0.0001	1.01	1.01E-01	<0.0001	-1.01	1.01E-01	<0.0001	1.01	1.01E-01	<0.0001	-1.01	1.01E-01	<0.0001	-1.01	1.01E-01	<0.0001	1.01	1.01E-01	<0.0001
Supplier	1	26	4.67	1.86E-02	<0.0001	-0.76	4.68E-01	<0.0001	2.42	1.12E-01	<0.0001	9.98	2.16E-04	<0.0001	-15.89	0.00E+00	<0.0001	28.29	1.94E-12	<0.0001	-0.76	4.68E-01	<0.0001	2.42	1.12E-01	<0.0001
Supplier	1	27	-38.44	0.00E+00	<0.0001	21.92	3.31E-09	<0.0001	5.75	3.15E-02	<0.0001	-0.93	3.95E-01	<0.0001	1.20	3.24E-00	<0.0001	-1.85	1.57E-01	<0.0001	21.92	3.31E-09	<0.0001	5.75	3.15E-02	<0.0001
Supplier	1	28	2.61	3.36E-01	<0.0001	-0.76	4.68E-01	<0.0001	2.42	1.12E-01	<0.0001	9.98	2.16E-04	<0.0001	-15.89	0.00E+00	<0.0001	28.29	1.94E-12	<0.0001	-0.76	4.68E-01	<0.0001	2.42	1.12E-01	<0.0001
Supplier	1	29	1.11	3.02E-00	<0.0001	-1.04	3.53E-01	<0.0001	0.73	2.08E-00	<0.0001	-0.82	4.42E-01	<0.0001	0.44	1.55E-00	<0.0001	-0.96	3.83E-01	<0.0001	-1.04	3.53E-01	<0.0001	0.73	2.08E-00	<0.0001
Supplier	1	30	4.81	1.23E-01	<0.0001	-0.31	6.95E-01	<0.0001	5.88	3.58E-02	<0.0001	10.28	1.39E-00	<0.0001	2.06	7.68E-00	<0.0001	-0.34	7.68E-01	<0.0001	-0.31	6.95E-01	<0.0001	5.88	3.58E-02	<0.0001
Supplier	1	31	5.09	1.62E-02	<0.0001	-0.34	7.09E-01	0.0232	5.95	3.62E-02	<0.0001	-0.12	8.91E-01	0.2811	2.82	1.69E-01	<0.0001	-1.26	2.83E-01	<0.0001	-0.34	7.09E-01	0.0301	2.82	1.69E-01	<0.0001
Supplier	1	32	0.33	1.60E-00	0.0257	0.64	1.90E-00	0.0069	3.47	3.20E-01	<0.0001	0.49	1.64E-01	0.0266	-0.59	5.58E-01	0.0016	0.51	1.66E-00	0.0038	0.64	1.90E-00	0.0069	3.47	3.20E-01	<0.0001
Supplier	1	33	1.95	5.95E-02	<0.0001	-1.95	5.95E-02	<0.0001	1.95	5.95E-02	<0.0001	-1.95	5.95E-02	<0.0001	1.95	5.95E-02	<0.0001	-1.95	5.95E-02	<0.0001	-1.95	5.95E-02	<0.0001	1.95	5.95E-02	<0.0001
Supplier	1	34	-3.84	2.29E-00	<0.0001	-5.18	1.69E-00	<0.0001	5.72	3.96E-02	<0.0001	-2.27	1.02E-01	<0.0001	7.71	2.25E-00	<0.0001	-7.10	6.06E-00	<0.0001	-5.18	1.69E-00	<0.0001	5.72	3.96E-02	<0.0001
Supplier	1	35	3.84	4.64E-01	<0.0001	0.77	2.18E-00	0.0002	-29.41	0.00E+00	<0.0001	1.55	4.72E-00	<0.0001	6.99	1.08E-03	<0.0001	2.06	7.62E-00	<0.0001	0.77	2.18E-00	0.0002	-29.41	0.00E+00	<0.0001
Supplier	1	36	-7.01	3.00E-04	<0.0001	-53.38	0.00E+00	<0.0001	-31.73	0.00E+00	<0.0001	-68.67	0.00E+00	<0.0001	-32.57	0.00E+00	<0.0001	-20.26	0.00E+00	<0.0001	-53.38	0.00E+00	<0.0001	-31.73	0.00E+00	<0.0001
Supplier																										

Table B.2: Summary results of full model (2 of 7).

Description	i	m	t1			t2			t3			t4			t5			t6			t7		
			β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value
Supplier	1	71	5.47	3.37E-02	<0.0001	2.55	1.28E-01	<0.0001	9.37	2.18E-04	<0.0001	2.57	1.94E-01	<0.0001	3.67	3.91E-01	<0.0001	0.36	1.44E+00	0.0151	3.76	2.32E-02	<0.0001
Supplier	1	72	5.94	1.58E-02	<0.0001	-4.45	1.17E-02	<0.0001	-11.57	0.00E+00	<0.0001	-4.23	2.41E-01	<0.0001	8.04	3.37E-03	<0.0001	-2.83	3.88E-02	<0.0001	-6.78	1.10E-03	<0.0001
Supplier	1	73	-1.99	1.37E-01	<0.0001	-30.35	0.00E+00	<0.0001	-48.83	0.00E+00	<0.0001	-42.13	0.00E+00	<0.0001	-8.28	0.00E+00	<0.0001	-41.33	0.00E+00	<0.0001	-20.88	1.03E-03	<0.0001
Supplier	1	74	0.40	1.98E+00	0.0128	-0.20	8.21E-01	0.1157	1.71	5.51E+00	<0.0001	-1.09	3.98E-01	<0.0001	0.73	2.08E+00	0.0003	-0.68	5.96E-01	0.0096	0.52	1.69E+00	0.0002
Supplier	1	75	2.45	1.99E+00	<0.0001	-0.55	5.78E-01	0.0025	9.77	1.74E+04	<0.0001	3.79	5.62E-01	<0.0001	4.44	8.68E-01	<0.0001	-2.33	9.78E-02	<0.0001	-0.80	4.48E-01	0.0002
Supplier	1	76	-15.07	0.00E+00	<0.0001	-1.38	2.06E-01	<0.0001	11.41	9.06E-04	<0.0001	-1.11	3.20E-01	<0.0001	4.44	8.68E-01	<0.0001	-2.33	9.78E-02	<0.0001	-1.38	2.06E-01	<0.0001
Supplier	1	77	-1.62	5.94E+00	<0.0001	-0.70	4.99E-01	0.0005	3.71	4.08E-01	<0.0001	1.32	3.75E+00	<0.0001	1.32	3.75E+00	<0.0001	-0.43	6.51E-01	0.0091	-0.23	7.98E-01	0.0046
Supplier	1	80	-2.67	6.92E-02	<0.0001	-0.94	3.92E-01	<0.0001	21.77	2.84E+09	<0.0001	2.44	1.14E-01	<0.0001	6.86	9.51E-02	<0.0001	14.57	2.13E-06	<0.0001	12.17	1.94E-03	<0.0001
Supplier	1	81	0.79	2.20E+00	<0.0001	6.52	6.77E-02	<0.0001	11.02	6.11E-04	<0.0001	4.94	3.39E-02	<0.0001	4.06	1.45E-02	<0.0001	8.27	3.89E+00	<0.0001	7.02	1.13E-03	<0.0001
Supplier	1	83	31.28	3.86E+13	<0.0001	17.44	3.78E+07	<0.0001	74.52	2.23E+32	<0.0001	23.77	2.11E+10	<0.0001	65.73	3.58E+28	<0.0001	18.47	1.05E+08	<0.0001	53.71	1.73E-22	<0.0001
Supplier	1	84	-8.22	3.00E-04	<0.0001	44.36	1.84E+19	<0.0001	-124.95	0.00E+00	<0.0001	23.33	1.68E+10	<0.0001	-33.32	0.00E+00	<0.0001	17.13	2.75E-07	<0.0001	23.76	2.09E+10	<0.0001
Supplier	1	85	-3.90	2.00E-02	<0.0001	-13.40	0.00E+00	<0.0001	-53.31	0.00E+00	<0.0001	-20.48	0.00E+00	<0.0001	-12.82	0.00E+00	<0.0001	-70.89	0.00E+00	<0.0001	-64.40	0.00E+00	<0.0001
Supplier	1	87	-1.33	3.78E+00	<0.0001	-2.03	1.33E-01	<0.0001	4.37	7.94E-01	<0.0001	-2.04	1.30E-01	<0.0001	-0.27	7.68E-01	0.5242	-3.09	4.58E-02	<0.0001	-3.24	3.92E-02	<0.0001
Supplier	1	88	29.60	7.13E+12	<0.0001	41.91	1.58E+18	<0.0001	-188.43	0.00E+00	<0.0001	10.06	1.90E+08	<0.0001	18.78	1.44E+08	<0.0001	10.70	4.43E+04	<0.0001	54.58	5.06E+23	<0.0001
Supplier	1	89	-6.19	2.00E+03	<0.0001	29.69	7.86E+12	<0.0001	329.56	1.33E+44	<0.0001	21.03	1.36E+09	<0.0001	27.10	5.86E+11	<0.0001	20.39	7.17E+08	<0.0001	39.31	2.15E+17	<0.0001
Supplier	1	91	-7.27	7.00E-04	<0.0001	-2.33	9.78E-02	<0.0001	14.36	1.72E+06	<0.0001	-1.51	1.64E-01	<0.0001	6.36	5.48E-02	<0.0001	-0.98	3.74E-01	<0.0001	-2.07	1.46E-01	<0.0001
Supplier	1	92	-7.88	4.00E-04	<0.0001	39.62	1.61E+17	<0.0001	14.74	2.32E+06	<0.0001	20.31	6.58E+08	<0.0001	-0.60	5.48E-01	0.0014	27.53	9.08E+11	<0.0001	70.76	5.37E+30	<0.0001
Supplier	1	93	-3.85	2.13E-02	<0.0001	-10.10	0.00E+00	<0.0001	-33.54	0.00E+00	<0.0001	-10.95	0.00E+00	<0.0001	-4.71	3.98E+03	<0.0001	-15.19	0.00E+00	<0.0001	-11.08	0.00E+00	<0.0001
Supplier	1	95	4.70	1.09E-02	<0.0001	-4.48	1.13E-02	<0.0001	-51.63	0.00E+00	<0.0001	-5.62	2.53E-02	<0.0001	2.73	1.53E+03	<0.0001	-4.54	1.07E-02	<0.0001	-6.01	2.46E-03	<0.0001
Supplier	1	96	4.02	5.53E-01	<0.0001	-11.99	0.00E+00	<0.0001	-80.69	0.00E+00	<0.0001	-5.62	3.60E-03	<0.0001	2.70	1.48E-01	<0.0001	-17.45	0.00E+00	<0.0001	-20.65	0.00E+00	<0.0001
Supplier	1	97	-7.86	4.00E-04	<0.0001	-1.83	1.61E-01	<0.0001	-33.38	0.00E+00	<0.0001	-12.77	3.81E-01	<0.0001	-35.60	0.00E+00	<0.0001	-1.78	1.68E-01	<0.0001	-2.38	2.92E-02	<0.0001
Supplier	1	99	-30.83	0.00E+00	<0.0001	12.83	3.72E+05	<0.0001	-188.47	0.00E+00	<0.0001	12.73	3.37E+05	<0.0001	-60.85	0.00E+00	<0.0001	10.50	3.62E+04	<0.0001	88.78	7.43E+29	<0.0001
Supplier	1	100	-20.34	0.00E+00	<0.0001	5.86	3.32E-02	<0.0001	67.54	2.16E+29	<0.0001	-2.44	8.72E-02	<0.0001	2.59	1.34E-01	<0.0001	-13.05	0.00E+00	<0.0001	-2.58	7.59E-02	<0.0001
Supplier	1	101	-5.48	4.20E-03	<0.0001	-1.89	1.32E-01	<0.0001	9.31	1.33E+04	<0.0001	-1.58	2.08E-01	<0.0001	2.16	8.68E+00	<0.0001	-2.03	1.33E-01	<0.0001	-2.27	1.04E-01	<0.0001
Supplier	1	102	-1.09	5.29E-01	<0.0001	-0.56	5.39E-01	<0.0001	-3.34	0.00E+00	<0.0001	-0.77	6.43E-01	<0.0001	-0.77	6.43E-01	<0.0001	-0.77	6.43E-01	<0.0001	-0.77	6.43E-01	<0.0001
Supplier	1	103	-16.03	0.00E+00	<0.0001	-16.21	0.00E+00	<0.0001	-46.58	0.00E+00	<0.0001	-14.68	0.00E+00	<0.0001	-47.96	0.00E+00	<0.0001	-26.02	0.00E+00	<0.0001	-27.94	0.00E+00	<0.0001
Supplier	1	104	29.60	7.13E+12	<0.0001	-46.13	0.00E+00	<0.0001	140.19	7.62E+60	<0.0001	28.80	3.23E+12	<0.0001	62.79	1.86E+27	<0.0001	12.92	4.08E-05	<0.0001	85.86	1.95E+37	<0.0001
Supplier	1	105	21.44	2.00E+09	<0.0001	-17.19	0.00E+00	<0.0001	-223.34	0.00E+00	<0.0001	-9.25	1.00E+04	<0.0001	42.23	2.18E+18	<0.0001	-24.56	0.00E+00	<0.0001	-34.21	0.00E+00	<0.0001
Supplier	1	107	-8.26	3.00E-04	<0.0001	15.61	6.03E-06	<0.0001	-23.94	0.00E+00	<0.0001	17.02	2.46E+07	<0.0001	-30.50	0.00E+00	<0.0001	31.36	1.47E-13	<0.0001	42.80	3.88E+18	<0.0001
Supplier	1	108	-1.49	2.28E-01	<0.0001	-0.66	5.13E-01	0.0008	-36.00	0.00E+00	<0.0001	-0.22	8.00E-01	0.0068	-23.80	0.00E+00	<0.0001	-1.32	1.47E-01	<0.0001	-2.46	8.53E-02	<0.0001
Supplier	1	109	19.81	7.86E+06	<0.0001	9.05	8.50E+03	<0.0001	-10.39	0.00E+00	<0.0001	21.29	1.77E+09	<0.0001	3.33	2.86E-01	<0.0001	10.62	4.00E+04	<0.0001	56.78	4.55E+24	<0.0001
Supplier	1	110	-1.49	2.28E-01	<0.0001	-0.66	5.13E-01	0.0008	-36.00	0.00E+00	<0.0001	-0.22	8.00E-01	0.0068	-23.80	0.00E+00	<0.0001	-1.32	1.47E-01	<0.0001	-2.46	8.53E-02	<0.0001
Supplier	1	111	-12.70	0.00E+00	<0.0001	-67.80	0.00E+00	<0.0001	-111.22	0.00E+00	<0.0001	-29.45	0.00E+00	<0.0001	-36.20	0.00E+00	<0.0001	-21.14	0.00E+00	<0.0001	-58.81	0.00E+00	<0.0001
Supplier	1	112	2.52	1.24E-01	<0.0001	-2.83	5.88E-02	<0.0001	-76.30	0.00E+00	<0.0001	-2.21	1.09E-01	<0.0001	1.68	5.34E+00	<0.0001	-2.59	7.53E-02	<0.0001	-3.19	4.13E-02	<0.0001
Supplier	1	113	2.12	8.34E-01	<0.0001	-0.50	6.90E-01	0.0044	8.10	3.28E+03	<0.0001	-0.20	8.16E-01	0.1072	2.89	1.86E-01	<0.0001	0.25	1.28E+00	0.0079	-0.27	7.64E-01	0.0023
Supplier	1	114	-3.36	1.24E-01	<0.0001	-1.39	1.24E-01	<0.0001	-6.18	4.82E+02	<0.0001	5.02	1.52E+02	<0.0001	3.43	3.09E-01	<0.0001	1.62	5.07E+00	<0.0001	-1.91	1.48E-01	<0.0001
Supplier	1	115	4.66	1.06E-02	<0.0001	5.64	2.83E-02	<0.0001	6.18	4.82E+02	<0.0001	20.43	7.44E+08	<0.0001	37.62	2.18E+16	<0.0001	37.82	1.21E+12	<0.0001	-25.19	0.00E+00	<0.0001
Supplier	1	116	3.98	5.37E-01	<0.0001	-13.18	0.00E+00	<0.0001	30.83	2.44E+13	<0.0001	-5.66	3.50E-03	<0.0001	21.84	8.32E+09	<0.0001	-4.27	1.40E-02	<0.0001	-3.08	4.60E-02	<0.0001
Supplier	1	117	-4.08	1.70E-02	<0.0001	-7.04	3.90E-04	<0.0001	-40.24	0.00E+00	<0.0001	-15.15	0.00E+00	<0.0001	-27.79	0.00E+00	<0.0001	-16.69	0.00E+00	<0.0001	-47.38	0.00E+00	<0.0001
Supplier	1	119	-6.56	1.40E-03	<0.0001	-18.59	0.00E+00	<0.0001	-37.25	0.00E+00	<0.0001	24.66	5.15E+10	<0.0001	-13.31	0.00E+00	<0.0001	25.22	9.01E+10	<0.0001	28.84	3.34E+12	<0.0001
Supplier	1	120	-1.51	2.22E-01	<0.0001	23.28	1.28E+10	<0.0001	21.08	1.48E+09	<0.0001	-2.74	6.90E-02	<0.0001	-0.84	4.31E-01	<0.0001	-12.30	0.00E+00	<0.0001	-8.30	1.00E+04	<0.0001
Supplier	1	121	-6.06	2.30E-03	<0.0001	-0.62	5.38E-01	0.0011	-29.20	4.82E+12	<0.0001	0.19	2.21E+00	0.1142	1.79	3.98E+00	<0.0001	33.88	3.46E+14	<0.0001	49.82	4.32E+21	<0.0001
Supplier	1	123	-2.09	1.24E-01	<0.0001	23.62	1.81E+10	<0.0001	14.21	1.40E+06	<0.0001	-0.93	3.96E-01	<0.0001	5.01	1.51E-02	<0.0001	-1.88	1.33E-01	<0.0001	-2.71	6.63E-02	<0.0001
Supplier	1	124	5.12	1.67E-02	<0.0001	-1.47	2.38E-01	<0.0001	7.81	2.47E+03	<0.0001	-3.50	2.22E-01	<0.0001	0.28	1.33E+00	0.0047	-1.35	2.66E-01	<0.0001	0.47	1.66E+00	0.0059
Supplier	1	125	-0.25	7.78E-01	0.8227	-0.65	5.21E-01	0.0008	7.81	2.47E+03	<0.0001												

Table B.3: Summary results of full model (3 of 7).

Description	i	m	t=1			t=2			t=3			t=4			t=5			t=6			t=7		
			β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value
PO Line Items	1	141	-5.34	4.82E-03	<0.0001	31.04	2.74E-14	<0.0001	-40.32	0.00E+00	<0.0001	21.15	1.88E-07	<0.0001	-28.83	0.02E-00	<0.0001	26.57	3.44E-11	<0.0001	69.39	1.37E-40	<0.0001
Supplier	1	142	23.34	1.37E-10	<0.0001	-32.67	0.00E+00	<0.0001	-1.45	2.35E-01	<0.0001	-12.49	7.02E-02	<0.0001	-12.49	7.02E-02	<0.0001	-42.70	0.00E+00	<0.0001	-52.57	0.00E+00	<0.0001
Supplier	1	143	-4.88	3.96E-01	<0.0001	-3.89	4.85E-02	<0.0001	-11.27	0.00E+00	<0.0001	9.89	2.18E-04	<0.0001	9.89	2.18E-04	<0.0001	-3.89	3.98E-02	<0.0001	-3.89	3.98E-02	<0.0001
Supplier	1	144	4.41	8.28E-01	<0.0001	-26.95	0.00E+00	<0.0001	-14.93	0.00E+00	<0.0001	-19.95	6.09E-07	<0.0001	-21.43	0.00E+00	<0.0001	-23.23	0.00E+00	<0.0001	-39.53	0.00E+00	<0.0001
Supplier	1	145	7.87	2.65E-03	<0.0001	16.95	2.31E-07	<0.0001	-115.04	0.00E+00	<0.0001	18.15	6.88E-07	<0.0001	18.15	6.88E-07	<0.0001	27.67	1.28E-12	<0.0001	54.19	3.41E-23	<0.0001
Supplier	1	147	-1.39	2.49E-01	<0.0001	-21.67	0.00E+00	<0.0001	-280.98	0.00E+00	<0.0001	-22.81	1.03E-00	<0.0001	-55.34	0.00E+00	<0.0001	-48.00	0.00E+00	<0.0001	-32.88	0.00E+00	<0.0001
Supplier	1	149	-5.78	3.19E-03	<0.0001	-2.33	9.79E-02	<0.0001	9.45	1.27E-04	<0.0001	-1.46	2.32E-01	<0.0001	1.40	4.07E-00	<0.0001	-2.35	9.55E-01	<0.0001	-3.76	1.32E-02	<0.0001
Supplier	1	150	-3.27	3.82E-02	<0.0001	29.87	9.34E-12	<0.0001	9.93	2.06E-04	<0.0001	10.70	4.43E-04	<0.0001	1.58	4.88E-00	<0.0001	26.22	2.44E-11	<0.0001	44.37	1.87E-19	<0.0001
Supplier	1	151	-2.56	1.29E-01	<0.0001	25.36	1.04E-11	<0.0001	99.25	1.27E-43	<0.0001	3.31	2.73E-01	<0.0001	53.40	1.56E-23	<0.0001	21.31	1.88E-09	<0.0001	15.01	3.30E-06	<0.0001
Supplier	1	152	-1.19	1.97E-01	<0.0001	-12.51	0.00E+00	<0.0001	-10.85	0.00E+00	<0.0001	34.24	7.43E-14	<0.0001	3.76	4.29E-01	<0.0001	49.98	2.06E-21	<0.0001	50.35	7.35E-21	<0.0001
Supplier	1	153	-9.30	7.43E-01	<0.0001	30.40	1.59E-13	<0.0001	25.19	8.70E-10	<0.0001	21.60	2.41E-09	<0.0001	42.04	0.00E+00	<0.0001	42.17	1.07E-18	<0.0001	76.70	2.05E-33	<0.0001
Supplier	1	154	-10.20	0.00E+00	<0.0001	47.75	5.45E-20	<0.0001	-103.58	0.00E+00	<0.0001	8.53	5.07E-03	<0.0001	8.53	5.07E-03	<0.0001	18.27	8.62E-07	<0.0001	74.84	3.18E-32	<0.0001
Supplier	1	155	-7.42	6.09E-04	<0.0001	48.36	1.25E-21	<0.0001	27.33	7.41E-11	<0.0001	17.69	4.81E-07	<0.0001	17.69	4.81E-07	<0.0001	18.27	8.62E-07	<0.0001	74.84	3.18E-32	<0.0001
Supplier	1	157	5.40	2.28E-02	<0.0001	1.32	7.41E-15	<0.0001	34.32	1.47E-15	<0.0001	-3.42	2.28E-02	<0.0001	-0.72	4.86E-01	<0.0001	24.10	2.94E-10	<0.0001	59.68	8.25E-25	<0.0001
PO Line Items	2	158	0.00	1.00E+00	0.9992	0.00	9.99E-01	0.9994	0.00	1.00E+00	0.9794	0.00	1.00E+00	0.9794	0.00	1.00E+00	0.9778	0.00	9.99E-01	0.9992	0.00	9.99E-01	0.9889
Supplier	2	159	0.00	1.00E+00	0.9991	0.00	9.99E-01	0.9989	0.00	1.00E+00	0.9752	0.00	1.00E+00	0.9752	0.00	1.00E+00	0.9778	0.00	9.99E-01	0.9989	0.00	9.99E-01	0.9815
Supplier	2	160	0.01	1.01E+00	0.8823	-0.13	8.72E-01	0.2524	0.39	1.47E+00	0.0347	-0.13	8.72E-01	0.2524	0.39	1.47E+00	0.0359	-0.33	2.22E-01	0.0282	-0.37	6.91E-01	0.0376
Level 1 Qualifications	3	162	-0.07	9.35E-01	0.7151	0.36	1.29E+00	0.0609	-0.16	8.51E-01	0.1712	0.36	1.43E+00	0.0195	-0.20	8.26E-01	0.1141	-0.17	8.45E-01	0.1158	-0.17	8.45E-01	0.1158
Supplier	3	163	0.38	2.48E-00	0.0183	0.30	1.35E+00	0.0382	0.60	1.95E+00	0.0013	0.30	1.35E+00	0.0394	0.22	1.25E+00	0.0593	-0.05	9.51E-01	0.5754	0.02	1.02E+00	0.3138
Supplier	3	164	-0.05	1.04E+00	0.9482	0.05	1.04E+00	0.9482	-0.05	1.04E+00	0.9482	-0.05	1.04E+00	0.9482	0.05	1.04E+00	0.9482	0.05	1.04E+00	0.9482	-0.05	1.04E+00	0.9482
Level 2 Qualifications	4	165	-2.07	1.27E-01	<0.0001	0.25	1.29E+00	0.0187	3.81	4.32E-01	<0.0001	-0.25	1.27E-01	<0.0001	0.24	1.28E+00	0.0687	0.06	1.06E+00	0.5116	-0.49	6.31E-01	0.0046
Supplier	4	166	-0.32	2.78E-01	<0.0001	0.13	1.14E+00	0.2464	0.78	2.18E+00	0.0002	-0.06	9.45E-01	0.5369	0.16	1.17E+00	0.1732	0.06	1.07E+00	0.4975	0.21	1.23E+00	0.1027
Supplier	4	167	0.38	2.48E+00	0.0183	0.30	1.35E+00	0.0382	3.52	3.95E-01	<0.0001	0.06	1.06E+00	0.5120	1.29	3.65E+00	<0.0001	0.38	2.75E-01	0.0449	-0.07	5.15E-01	0.0007
Supplier	4	168	0.15	1.15E+00	0.2133	-0.17	8.45E-01	0.1589	0.70	2.01E+00	0.0025	-0.13	8.72E-01	0.2172	0.18	1.15E+00	0.1438	-0.17	8.45E-01	0.1570	-0.19	8.22E-01	0.1189
Core Competency	5	170	12.33	2.27E-05	<0.0001	28.34	2.04E-12	<0.0001	89.51	8.25E-38	<0.0001	26.82	4.45E-11	<0.0001	23.79	1.15E-10	<0.0001	33.79	4.74E-14	<0.0001	46.63	1.78E-20	<0.0001
Supplier	5	171	4.64	1.04E-02	<0.0001	-0.07	9.35E-01	0.4700	0.29	1.34E+00	0.0411	15.59	5.92E-06	<0.0001	8.67	5.80E-03	<0.0001	7.37	1.59E-03	<0.0001	-0.15	8.64E-01	0.2024
Supplier	5	172	0.35	7.08E-01	0.0209	-0.19	8.25E-01	0.1245	1.89	6.59E+00	<0.0001	-0.33	2.71E-01	0.0305	-0.02	9.76E-01	0.781	0.01	1.01E+00	0.9326	-0.02	9.76E-01	0.7724
Core Competency	6	173	0.35	7.08E-01	0.0209	-0.19	8.25E-01	0.1245	1.89	6.59E+00	<0.0001	-0.33	2.71E-01	0.0305	-0.02	9.76E-01	0.781	0.01	1.01E+00	0.9326	-0.02	9.76E-01	0.7724
Core Competency	7	174	4.86	1.29E-02	<0.0001	4.14	6.28E-01	<0.0001	-41.44	0.00E+00	<0.0001	22.85	8.43E-09	<0.0001	-3.07	4.65E-02	<0.0001	23.84	1.37E-10	<0.0001	-19.67	0.00E+00	<0.0001
Core Competency	8	175	0.69	1.99E+00	0.0005	-0.54	5.82E-01	0.0027	2.33	1.88E+00	<0.0001	-0.25	7.79E-01	0.0647	0.74	2.09E+00	0.0003	-0.35	5.79E-01	0.0025	-1.13	3.22E-01	<0.0001
Core Competency	9	176	0.69	1.99E+00	0.0005	-0.54	5.82E-01	0.0027	2.33	1.88E+00	<0.0001	-0.25	7.79E-01	0.0647	0.74	2.09E+00	0.0003	-0.35	5.79E-01	0.0025	-1.13	3.22E-01	<0.0001
Core Competency	10	177	0.67	1.66E+00	0.0057	0.73	2.07E+00	0.0003	-4.84	9.70E-03	<0.0001	1.60	4.96E+00	<0.0001	-0.08	3.26E-01	0.4267	1.98	7.22E+00	<0.0001	0.14	1.15E+00	0.1129
Core Competency	11	178	-10.62	0.00E+00	<0.0001	5.27	1.95E-02	<0.0001	3.68	3.95E-01	<0.0001	4.21	6.72E-01	<0.0001	0.40	1.49E+00	0.0124	3.81	4.50E-01	<0.0001	8.59	8.01E-03	<0.0001
Core Competency	12	179	17.62	4.56E-07	<0.0001	35.20	1.94E-15	<0.0001	-22.16	0.00E+00	<0.0001	27.25	6.81E-11	<0.0001	36.67	8.44E-15	<0.0001	53.80	2.32E-23	<0.0001	41.46	1.01E-18	<0.0001
Core Competency	13	180	0.38	2.48E+00	0.0183	0.30	1.35E+00	0.0382	3.52	3.95E-01	<0.0001	0.06	1.06E+00	0.5120	1.29	3.65E+00	<0.0001	0.38	2.75E-01	0.0449	-0.07	5.15E-01	0.0007
Core Competency	14	181	2.45	1.16E-01	<0.0001	6.74	8.43E-01	<0.0001	5.99	2.41E-02	<0.0001	-0.01	9.97E-01	0.8626	2.57	1.33E+00	<0.0001	-0.77	4.44E-01	0.0002	-1.06	3.46E-01	<0.0001
Core Competency	15	182	2.84	1.71E-01	<0.0001	-1.26	2.88E-01	<0.0001	4.43	8.84E-01	<0.0001	-0.16	8.49E-01	0.1871	0.30	1.35E+00	0.0370	0.15	1.16E+00	0.1924	0.55	1.74E+00	0.0023
Core Competency	16	183	-1.68	1.86E-01	<0.0001	7.22	1.37E+00	<0.0001	-2.46	8.31E-02	<0.0001	5.67	2.50E-02	<0.0001	-14.93	0.00E+00	<0.0001	-1.25	2.86E-01	<0.0001	0.06	1.06E+00	0.5449
Core Competency	17	184	1.56	1.47E-00	<0.0001	1.56	1.47E-00	<0.0001	7.08	1.18E-03	<0.0001	-1.35	2.58E-01	<0.0001	7.08	1.18E-03	<0.0001	-1.35	2.58E-01	<0.0001	-1.06	3.46E-01	<0.0001
Core Competency	18	185	0.59	1.81E+00	0.0016	-0.24	1.88E-01	0.0730	-1.80	1.80E+00	<0.0001	-1.49	2.23E-01	<0.0001	-5.43	4.46E-03	<0.0001	-1.88	1.33E-01	<0.0001	0.65	1.91E+00	0.0009
Core Competency	19	186	0.60	1.83E+00	0.0014	0.20	1.22E+00	0.1170	-1.80	1.80E+00	<0.0001	-1.49	2.23E-01	<0.0001	-5.43	4.46E-03	<0.0001	-1.88	1.33E-01	<0.0001			

Table B.5: Summary results of full model (5 of 7).

Description	I	R	T1		T2		T3		T4		T5		T6		T7		
			B	CR	B	CR	B	CR	B	CR	B	CR	B	CR	B	CR	
Commodity	36	281	4.89	1.35E-02	<0.0001	17.01	2.45E-07	<0.0001	-75.56	0.00E+00	<0.0001	17.27	3.15E-07	<0.0001	-15.08	0.00E+00	<0.0001
Commodity	36	282	-4.30	1.38E-02	<0.0001	-2.03	1.31E-01	<0.0001	0.36	1.49E-00	0.0039	-1.01	3.62E-01	<0.0001	22.76	7.64E-09	<0.0001
Commodity	36	283	1.16	1.18E-00	0.2842	-0.11	8.92E-01	0.2842	-1.16	1.31E-01	<0.0001	-0.78	6.17E-02	<0.0001	-0.64	1.97E-01	<0.0001
Commodity	36	284	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Commodity	36	285	-5.13	5.90E-03	<0.0001	3.67	3.93E-01	<0.0001	-38.28	0.00E+00	<0.0001	1.92	8.06E-03	<0.0001	2.22	5.17E-00	<0.0001
Commodity	36	286	1.66	5.28E-00	<0.0001	3.31	3.94E-01	<0.0001	3.31	3.94E-01	<0.0001	0.55	1.70E-00	<0.0001	0.89	2.90E+00	<0.0001
Commodity	36	287	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Commodity	36	288	-0.34	7.15E-01	0.0241	-2.84	5.84E-02	<0.0001	-14.75	0.00E+00	<0.0001	-0.50	6.07E-01	<0.0001	0.80	2.00E-04	<0.0001
Commodity	36	290	-2.40	9.09E-02	<0.0001	46.72	1.94E-20	<0.0001	8.13	3.98E-03	<0.0001	48.65	1.94E-20	<0.0001	4.30	7.34E-01	<0.0001
Commodity	36	291	-8.69	2.06E-04	<0.0001	17.85	5.63E-07	<0.0001	24.67	5.20E-10	<0.0001	11.25	7.71E-04	<0.0001	10.00	2.20E-04	<0.0001
Commodity	36	292	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Commodity	36	293	4.79	1.20E-04	<0.0001	0.20	1.24E-00	0.1060	3.10	2.21E-01	<0.0001	0.23	2.52E-00	0.0841	-0.32	7.24E-01	0.0297
Commodity	36	294	10.16	2.58E-04	<0.0001	-0.89	4.09E-01	<0.0001	8.01	3.02E-03	<0.0001	-0.18	8.38E-01	0.1485	8.19	3.62E-03	<0.0001
Commodity	36	295	-1.56	2.10E-01	<0.0001	-2.73	6.59E-02	<0.0001	0.02	1.02E-00	0.9729	-2.76	6.34E-02	<0.0001	-0.54	5.85E-01	0.0028
Commodity	36	296	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Commodity	36	297	-0.29	7.52E-01	0.0438	1.07	2.93E-00	<0.0001	5.97	3.55E-02	<0.0001	1.37	3.95E-00	<0.0001	0.62	1.86E-00	0.0011
Commodity	36	298	6.04	4.20E-02	<0.0001	7.54	1.89E-03	<0.0001	-4.75	8.70E-03	<0.0001	8.53	5.96E-03	<0.0001	9.21	1.00E-04	<0.0001
Commodity	36	299	3.32	1.78E-01	<0.0001	0.69	1.99E-00	0.0005	-2.69	6.78E-02	<0.0001	2.66	1.48E-01	<0.0001	2.75	1.57E-01	<0.0001
Commodity	36	300	-5.83	2.95E-03	<0.0001	-2.56	7.75E-02	<0.0001	-27.51	0.00E+00	<0.0001	-13.02	0.00E+00	<0.0001	-8.89	2.65E-02	<0.0001
Commodity	36	301	-1.51	2.22E-01	<0.0001	23.28	1.28E-10	<0.0001	-37.25	0.00E+00	<0.0001	24.66	5.15E-10	<0.0001	25.22	5.01E-10	<0.0001
Commodity	36	302	52.34	5.41E-22	<0.0001	26.09	2.15E-11	<0.0001	-3.56	2.84E-02	<0.0001	2.74	1.55E-01	<0.0001	32.13	9.02E-13	<0.0001
Commodity	36	303	1.85	6.55E-01	<0.0001	4.00	5.45E-01	<0.0001	-0.86	5.17E-01	0.0007	3.71	4.10E-00	<0.0001	0.33	1.93E-00	0.0271
Item/Service Identifier	37	305	0.09	1.09E-00	0.3726	2.64	1.64E-01	<0.0001	-0.39	6.78E-01	0.0443	2.37	1.07E-01	<0.0001	-0.02	9.84E-01	0.8251
Item/Service Identifier	37	306	-0.90	4.08E-01	<0.0001	2.49	1.20E-01	<0.0001	-0.23	7.97E-01	0.0621	2.18	8.83E-00	<0.0001	-0.57	3.78E-01	<0.0001
Item/Service Identifier	37	307	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Item/Service Identifier	37	308	-0.29	7.52E-01	0.0438	1.07	2.93E-00	<0.0001	5.97	3.55E-02	<0.0001	1.37	3.95E-00	<0.0001	0.62	1.86E-00	0.0011
Item/Service Identifier	37	309	-0.29	7.52E-01	0.0438	1.07	2.93E-00	<0.0001	5.97	3.55E-02	<0.0001	1.37	3.95E-00	<0.0001	0.62	1.86E-00	0.0011
Item/Service Identifier	37	310	-4.55	1.06E-02	<0.0001	-36.54	0.00E+00	<0.0001	2.79	1.63E-01	<0.0001	-37.53	0.00E+00	<0.0001	1.56	4.77E-00	<0.0001
Item/Service Identifier	37	311	-0.71	4.92E-01	0.0004	-91.39	0.00E+00	<0.0001	131.33	1.08E-57	<0.0001	-30.05	0.00E+00	<0.0001	14.65	3.30E-06	<0.0001
Item/Service Identifier	37	312	-1.51	2.22E-01	<0.0001	23.28	1.28E-10	<0.0001	-37.25	0.00E+00	<0.0001	24.66	5.15E-10	<0.0001	25.22	5.01E-10	<0.0001
Item/Service Identifier	37	313	-11.54	0.00E+00	<0.0001	-41.33	0.00E+00	<0.0001	-25.20	0.00E+00	<0.0001	-34.66	0.00E+00	<0.0001	-38.27	0.00E+00	<0.0001
Item/Service Identifier	37	314	-0.52	5.92E-01	0.0032	-13.63	0.00E+00	<0.0001	10.34	3.11E-04	<0.0001	-19.47	0.00E+00	<0.0001	8.78	6.48E-03	<0.0001
Item Family	38	315	-6.08	2.36E-03	<0.0001	-0.71	4.92E-01	0.0004	-55.40	0.00E+00	<0.0001	-0.93	3.96E-01	<0.0001	-34.22	0.00E+00	<0.0001
Item Family	38	316	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Item Family	38	317	10.18	2.68E-04	<0.0001	12.15	1.89E-05	<0.0001	18.72	1.34E-08	<0.0001	5.35	2.05E-00	<0.0001	9.82	1.84E-04	<0.0001
Item Family	38	318	-9.12	1.00E-04	<0.0001	1.01	2.74E-00	<0.0001	5.94	3.09E-02	<0.0001	-3.19	4.10E-02	<0.0001	0.88	2.42E-00	<0.0001
Item Family	38	319	-3.01	0.00E+00	<0.0001	-22.54	0.00E+00	<0.0001	-8.55	2.00E-04	<0.0001	-21.14	0.00E+00	<0.0001	-24.74	0.00E+00	<0.0001
Item Family	38	320	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Item Family	38	321	-0.62	3.46E-01	0.0012	5.80	3.31E-02	<0.0001	-5.89	2.80E-03	<0.0001	3.84	4.67E-00	<0.0001	-9.90	1.00E-04	<0.0001
Item Family	38	322	14.94	3.09E-06	<0.0001	22.04	3.75E-09	<0.0001	29.86	7.58E-12	<0.0001	14.88	2.89E-06	<0.0001	17.57	4.25E-07	<0.0001
Item Family	38	323	4.18	6.57E-01	<0.0001	21.54	2.26E-09	<0.0001	2.34	1.04E-01	<0.0001	14.27	1.57E-06	<0.0001	-1.16	3.14E-02	<0.0001
Item Family	38	324	-0.90	4.08E-01	<0.0001	2.49	1.20E-01	<0.0001	-0.23	7.97E-01	0.0621	2.18	8.83E-00	<0.0001	-0.57	3.78E-01	<0.0001
Item Family	38	325	-13.26	0.00E+00	<0.0001	-41.33	0.00E+00	<0.0001	-25.20	0.00E+00	<0.0001	-34.66	0.00E+00	<0.0001	-38.27	0.00E+00	<0.0001
Item Family	38	326	36.00	4.30E-15	<0.0001	4.84	1.27E-02	<0.0001	4.45	6.60E-01	<0.0001	16.53	2.26E-07	<0.0001	16.78	1.94E-07	<0.0001
Item Family	38	327	-12.40	0.00E+00	<0.0001	-21.58	0.00E+00	<0.0001	-19.78	0.00E+00	<0.0001	-10.28	0.00E+00	<0.0001	-9.74	1.00E-04	<0.0001
Item Family	38	328	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Item Family	38	329	3.21	2.48E-01	<0.0001	1.16	3.16E-00	<0.0001	0.98	2.66E-00	<0.0001	2.16	6.69E-00	<0.0001	1.44	5.17E-00	<0.0001
Item Family	38	330	-0.19	8.23E-01	0.1182	-2.03	7.48E-01	0.0417	0.86	2.37E-00	<0.0001	-0.45	6.35E-01	0.0669	0.14	1.16E-00	0.2051
Item Family	38	331	-4.30	1.38E-02	<0.0001	-2.03	1.31E-01	<0.0001	0.36	1.49E-00	0.0039	-1.01	3.62E-01	<0.0001	-2.78	6.17E-02	<0.0001
Item Family	38	332	0.44	1.55E-00	0.0082	3.21	2.48E-01	0.0082	5.94	6.95E-03	<0.0001	2.78	1.60E-00	<0.0001	0.59	5.29E-01	0.0059
Item Family	38	333	-0.45	4.33E-01	0.0069	0.37	7.96E-00	0.0076	0.15	1.23E-00	0.8855	0.34	8.41E-00	0.0238	0.21	8.08E-01	0.0973
Item Family	38	334	-0.84	4.33E-01	0.0069	0.37	7.96E-00	0.0076	0.15	1.23E-00	0.8855	0.34	8.41E-00	0.0238	0.21	8.08E-01	0.0973
Item Family	38	335	-23.32	0.00E+00	<0.0001	-47.47	0.00E+00	<0.0001	-51.13	0.00E+00	<0.0001	-47.55	0.00E+00	<0.0001	-26.34	0.00E+00	<0.0001
Item Family	38	336	-1.96	5.84E-02	<0.0001	1.96	5.84E-02	<0.0001	-3.28	3.94E-01	<0.0001	0.55	1.74E-00	<0.0001	0.85	2.28E+00	<0.0001
Item Family	38	337	1.16	5.28E-00	<0.0001	1.72	5.61E-00	<0.0001	3.33	3.94E-01	<						

Table B.6: Summary results of full model (6 of 7).

	m1		m2		m3		m4		m5		m6		m7	
	β	P-value	β	P-value	β	P-value	β	P-value	β	P-value	β	P-value	β	P-value
Item Family	38	351	-5.83	<0.0001	-2.56	<0.0001	-27.51	<0.0001	-3.18	<0.0001	-18.02	<0.0001	-3.63	<0.0001
Item Family	38	352	-1.51	<0.0001	23.28	<0.0001	-37.25	<0.0001	24.66	<0.0001	-13.31	<0.0001	25.22	<0.0001
Item Family	38	353	52.34	<0.0001	26.09	<0.0001	-3.56	<0.0001	2.74	<0.0001	31.33	<0.0001	23.36	<0.0001
Service Family	39	355	-6.08	<0.0001	-0.71	<0.0001	-55.40	<0.0001	-0.93	<0.0001	-44.22	<0.0001	-1.11	<0.0001
Service Family	39	356	-0.25	<0.0001	0.84	<0.0001	0.34	<0.0001	1.76	<0.0001	1.76	<0.0001	3.28	<0.0001
Service Family	39	357	-4.11	<0.0001	-4.75	<0.0001	-6.61	<0.0001	-2.24	<0.0001	-3.63	<0.0001	-3.61	<0.0001
Service Family	39	358	15.58	<0.0001	11.83	<0.0001	5.54	<0.0001	11.33	<0.0001	6.21	<0.0001	12.38	<0.0001
Service Family	39	359	15.58	<0.0001	11.83	<0.0001	5.54	<0.0001	11.33	<0.0001	6.21	<0.0001	12.38	<0.0001
Service Family	39	360	-0.88	<0.0001	7.31	<0.0001	6.75	<0.0001	-0.40	<0.0001	-0.46	<0.0001	0.13	<0.0001
Service Family	39	361	6.58	<0.0001	-0.02	<0.0001	5.56	<0.0001	3.06	<0.0001	6.13	<0.0001	3.52	<0.0001
Service Family	39	362	-0.88	<0.0001	-0.02	<0.0001	5.56	<0.0001	3.06	<0.0001	6.13	<0.0001	3.52	<0.0001
Service Family	39	363	-1.75	<0.0001	-10.37	<0.0001	-0.74	<0.0001	-7.11	<0.0001	1.33	<0.0001	-9.86	<0.0001
Service Family	39	364	-2.24	<0.0001	-11.36	<0.0001	-0.12	<0.0001	1.47	<0.0001	-6.45	<0.0001	5.59	<0.0001
Service Family	39	365	-2.22	<0.0001	-5.57	<0.0001	-0.30	<0.0001	-3.10	<0.0001	-3.39	<0.0001	-3.76	<0.0001
Service Family	39	366	4.89	<0.0001	17.01	<0.0001	2.45	<0.0001	17.27	<0.0001	-15.08	<0.0001	22.76	<0.0001
Service Family	39	367	-0.19	<0.0001	-0.29	<0.0001	-0.86	<0.0001	0.45	<0.0001	0.14	<0.0001	-0.58	<0.0001
Service Family	39	368	4.89	<0.0001	17.01	<0.0001	2.45	<0.0001	17.27	<0.0001	-15.08	<0.0001	22.76	<0.0001
Service Family	39	369	6.58	<0.0001	3.26	<0.0001	-0.38	<0.0001	-0.31	<0.0001	3.78	<0.0001	3.07	<0.0001
Service Family	39	370	11.96	<0.0001	0.37	<0.0001	0.11	<0.0001	0.94	<0.0001	-0.21	<0.0001	0.42	<0.0001
Service Family	39	371	1.06	<0.0001	0.30	<0.0001	-5.02	<0.0001	3.42	<0.0001	-5.43	<0.0001	-3.23	<0.0001
Service Family	39	372	-2.40	<0.0001	-4.62	<0.0001	8.13	<0.0001	-4.65	<0.0001	4.30	<0.0001	60.27	<0.0001
Service Family	39	373	1.13	<0.0001	-2.73	<0.0001	0.02	<0.0001	-2.78	<0.0001	-0.54	<0.0001	-4.68	<0.0001
Service Family	39	374	-1.56	<0.0001	2.16	<0.0001	0.02	<0.0001	0.02	<0.0001	0.02	<0.0001	0.02	<0.0001
Service Family	39	375	-1.56	<0.0001	2.16	<0.0001	0.02	<0.0001	0.02	<0.0001	0.02	<0.0001	0.02	<0.0001
Service Family	39	376	-0.29	<0.0001	0.04	<0.0001	5.87	<0.0001	1.37	<0.0001	1.37	<0.0001	0.62	<0.0001
Service Family	39	377	2.86	<0.0001	1.07	<0.0001	-5.22	<0.0001	2.80	<0.0001	1.89	<0.0001	10.80	<0.0001
Service Family	39	378	2.86	<0.0001	1.07	<0.0001	-5.22	<0.0001	2.80	<0.0001	1.89	<0.0001	10.80	<0.0001
Program	40	379	1.66	<0.0001	0.48	<0.0001	0.60	<0.0001	0.44	<0.0001	0.22	<0.0001	0.12	<0.0001
Program	40	380	0.28	<0.0001	0.13	<0.0001	0.32	<0.0001	0.06	<0.0001	0.11	<0.0001	0.01	<0.0001
Program	40	381	-13.00	<0.0001	-42.64	<0.0001	10.01	<0.0001	30.74	<0.0001	70.29	<0.0001	59.97	<0.0001
Program	40	382	11.96	<0.0001	15.41	<0.0001	-1.45	<0.0001	-19.59	<0.0001	-10.35	<0.0001	-29.23	<0.0001
Program	40	383	21.25	<0.0001	15.41	<0.0001	4.63	<0.0001	85.64	<0.0001	-10.35	<0.0001	29.23	<0.0001
Program	40	384	12.31	<0.0001	85.63	<0.0001	10.08	<0.0001	129.14	<0.0001	-7.28	<0.0001	174.94	<0.0001
Program	40	385	4.71	<0.0001	20.56	<0.0001	54.40	<0.0001	9.93	<0.0001	19.98	<0.0001	20.32	<0.0001
Program	40	386	19.98	<0.0001	9.93	<0.0001	20.32	<0.0001	19.98	<0.0001	9.93	<0.0001	20.32	<0.0001
Program	40	387	19.98	<0.0001	9.93	<0.0001	20.32	<0.0001	19.98	<0.0001	9.93	<0.0001	20.32	<0.0001
Program	40	388	-11.98	<0.0001	-48.75	<0.0001	-79.38	<0.0001	-16.18	<0.0001	-34.87	<0.0001	-31.59	<0.0001
Program	40	389	0.65	<0.0001	0.07	<0.0001	1.12	<0.0001	0.24	<0.0001	0.02	<0.0001	0.61	<0.0001
Program	40	390	0.65	<0.0001	0.07	<0.0001	1.12	<0.0001	0.24	<0.0001	0.02	<0.0001	0.61	<0.0001
Program	40	391	0.69	<0.0001	1.89	<0.0001	1.99	<0.0001	0.83	<0.0001	0.33	<0.0001	1.20	<0.0001
Program	40	392	-21.59	<0.0001	-72.76	<0.0001	-38.41	<0.0001	25.66	<0.0001	-57.90	<0.0001	18.49	<0.0001
Program	40	393	0.10	<0.0001	0.78	<0.0001	11.21	<0.0001	0.07	<0.0001	0.75	<0.0001	0.30	<0.0001
Program	40	394	0.10	<0.0001	0.78	<0.0001	11.21	<0.0001	0.07	<0.0001	0.75	<0.0001	0.30	<0.0001
Program	40	395	-12.16	<0.0001	-35.21	<0.0001	81.82	<0.0001	1.18	<0.0001	68.65	<0.0001	68.68	<0.0001
Program	40	396	-0.48	<0.0001	0.31	<0.0001	-113.07	<0.0001	0.12	<0.0001	0.50	<0.0001	0.21	<0.0001
Program	40	397	-12.41	<0.0001	-37.2	<0.0001	37.2	<0.0001	3.11	<0.0001	-41.07	<0.0001	2.55	<0.0001
Program	40	398	-12.41	<0.0001	-37.2	<0.0001	37.2	<0.0001	3.11	<0.0001	-41.07	<0.0001	2.55	<0.0001
Program	40	399	1.51	<0.0001	0.90	<0.0001	2.28	<0.0001	0.65	<0.0001	0.05	<0.0001	1.11	<0.0001
Program	40	400	3.08	<0.0001	2.38	<0.0001	-0.09	<0.0001	1.04	<0.0001	0.69	<0.0001	0.68	<0.0001
Program	40	401	-16.65	<0.0001	-145.87	<0.0001	1.12	<0.0001	-84.54	<0.0001	-1.56	<0.0001	-80.82	<0.0001
Program	40	402	-16.65	<0.0001	-145.87	<0.0001	1.12	<0.0001	-84.54	<0.0001	-1.56	<0.0001	-80.82	<0.0001
Program	40	403	-18.85	<0.0001	-61.34	<0.0001	-38.26	<0.0001	-14.38	<0.0001	-34.64	<0.0001	-32.36	<0.0001
Program	40	404	-18.85	<0.0001	-61.34	<0.0001	-38.26	<0.0001	-14.38	<0.0001	-34.64	<0.0001	-32.36	<0.0001
Program	40	405	-18.07	<0.0001	-48.04	<0.0001	2.46	<0.0001	-13.75	<0.0001	0.36	<0.0001	0.54	<0.0001
Program	40	406	-18.07	<0.0001	-48.04	<0.0001	2.46	<0.0001	-13.75	<0.0001	0.36	<0.0001	0.54	<0.0001
Program	40	407	2.58	<0.0001	1.34	<0.0001	2.71	<0.0001	0.24	<0.0001	1.46	<0.0001	0.66	<0.0001
Program	40	408	-10.38	<0.0001	-34.34	<0.0001	-34.92	<0.0001	-15.28	<0.0001	-33.84	<0.0001	-33.44	<0.0001
Program	40	409	-11.95	<0.0001	-2.04	<0.0001	1.74	<0.0001	0.89	<0.0001	0.34	<0.0001	0.96	<0.0001
Program	40	410	-11.95	<0.0001	-2.04	<0.0001	1.74	<0.0001	0.89	<0.0001	0.34	<0.0001	0.96	<0.0001
Program	40	411	-10.19	<0.0001	5.80	<0.0001	-47.41	<0.0001	4.28	<0.0001	-32.26	<0.0001	4.60	<0.0001
Program	40	412	2.81	<0.0001	2.89	<0.0001	-35.78	<0.0001	3.37	<0.0001	1.64	<0.0001	2.50	<0.0001
Program	40	413	-15.09	<0.0001	-0.83	<0.0001	-66.15	<0.0001	-1.35	<0.0001	-49.19	<0.0001	-2.24	<0.0001
Program	40	414	-15.09	<0.0001	-0.83	<0.0001	-66.15	<0.0001	-1.35	<0.0001	-49.19	<0.0001	-2.24	<0.0001
Program	40	415	-15.09	<0.0001	-0.83	<0.0001	-66.15	<0.0001	-1.35	<0.0001	-49.19	<0.0001	-2.24	<0.0001
Program	40	416	1.43	<0.0001	0.31	<0.0001	2.49	<0.0001	0.30	<0.0001	0.93	<0.0001	0.01	<0.0001
Program	40	417	-15.09	<0.0001	-0.83	<0.0001	-66.15	<0.0001	-1.35	<0.0001	-49.19	<0.0001	-2.24	<0.0001
Program	40	418	-15.09	<0.0001	-0.83	<0.0001	-66.15	<0.0001	-1.35	<0.0001	-49.19	<0.0001	-2.24	<0.0001
Program	40	419	1.26	<0.0001	1.26	<0.0001	2.06	<0.0001	0.38	<0.0001	0.38	<0.0001	0.38	

Table B.7: Summary results of full model (7 of 7).

Description	I	m	r1			r2			r3			r4			r5			r6			r7		
			β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value	β	OR	P-value
Program	40	421	0.21	1.28E+00	0.1548	0.16	1.17E+00	0.1773	2.56	1.30E+01	<0.0001	-0.17	8.44E-01	0.1554	1.13	3.10E+00	<0.0001	-0.34	7.15E-01	0.0254	-0.05	5.21E-01	0.0008
Program	40	422	0.37	1.48E+00	0.0375	-41.05	0.00E+00	<0.0001	4.16	6.42E+01	<0.0001	-10.07	0.00E+00	<0.0001	2.70	1.40E+01	<0.0001	0.36	1.48E+00	0.0002	0.11	1.84E+00	0.0346
Program	40	423	1.21	3.98E+00	<0.0001	1.23	3.44E+00	<0.0001	0.09	1.08E+00	0.7335	0.65	1.91E+00	0.0089	-0.02	3.77E-01	0.7741	-0.20	8.17E-01	0.1087	-0.28	7.55E-01	0.0488
Program	40	424	0.48	1.62E+00	0.0001	0.49	1.62E+00	0.0001	1.29	3.39E+00	<0.0001	1.29	3.39E+00	<0.0001	1.49	4.42E+00	<0.0001	0.54	1.72E+00	0.0027	0.03	1.08E+00	0.7319
Program	40	425	2.44	1.58E+01	<0.0001	1.40	4.07E+00	<0.0001	1.67	5.31E+00	<0.0001	1.08	1.08E+00	0.1129	-0.34	7.14E-01	0.0249	-0.47	6.27E-01	0.0060	-0.59	1.54E+00	0.0016
Program	40	426	0.47	1.66E+00	0.0060	0.89	2.48E+00	<0.0001	0.11	1.11E+00	0.1166	0.08	1.08E+00	0.4129	-0.34	7.14E-01	0.0249	-0.47	6.27E-01	0.0060	-0.59	1.54E+00	0.0016
Program	40	427	-1.71	1.82E+01	<0.0001	-3.19	4.13E+02	<0.0001	-40.41	0.00E+00	<0.0001	-10.99	0.00E+00	<0.0001	-11.31	0.00E+00	<0.0001	-17.85	0.00E+00	<0.0001	-16.57	0.00E+00	<0.0001
Program	40	428	0.28	1.22E+00	0.0001	0.28	1.22E+00	0.0001	-0.87	4.20E-01	0.0001	0.49	1.48E+00	0.0049	-1.83	1.61E-01	<0.0001	0.40	1.48E+00	0.0126	0.57	1.76E+00	0.0020
Program	40	429	-14.92	0.00E+00	<0.0001	0.84	2.36E+00	0.0001	-0.87	4.20E-01	0.0001	0.49	1.48E+00	0.0049	-1.83	1.61E-01	<0.0001	0.40	1.48E+00	0.0126	0.57	1.76E+00	0.0020
Program	40	430	-13.67	0.00E+00	<0.0001	-0.12	8.98E-01	0.7287	0.39	1.48E+00	0.0137	-0.40	6.70E-01	0.0224	-0.59	3.72E-01	<0.0001	-0.11	9.06E-01	0.3165	0.01	1.01E+00	0.8514
Program	40	431	-12.95	0.00E+00	<0.0001	31.89	7.05E+13	<0.0001	-83.13	0.00E+00	<0.0001	3.73	4.15E+01	<0.0001	-11.01	0.00E+00	<0.0001	28.48	2.36E+12	<0.0001	41.85	1.22E+18	<0.0001
Program	40	432	0.18	1.18E+00	0.1169	0.65	1.91E+00	0.0008	0.34	1.27E+00	0.0713	0.58	1.48E+00	0.0382	-0.01	3.81E-01	0.8884	0.36	1.27E+00	0.0529	0.32	1.86E+00	0.0291
Program Family	41	434	0.28	1.32E+00	0.0481	0.13	1.13E+00	0.2522	0.32	1.38E+00	0.0303	0.06	1.06E+00	0.5158	0.01	1.01E+00	0.9046	0.03	1.03E+00	0.7059	-0.02	9.79E-01	0.7943
Program Family	41	435	-3.30	3.70E+02	<0.0001	13.97	1.17E+06	<0.0001	31.11	3.24E+13	<0.0001	5.04	1.58E+02	<0.0001	3.34	2.81E+01	<0.0001	5.18	1.77E+02	<0.0001	13.64	8.37E+05	<0.0001
Program Family	41	436	0.06	1.06E+00	0.0001	0.06	1.06E+00	0.0001	-0.04	9.65E-01	0.6781	-0.04	9.65E-01	0.6781	1.81	4.12E+00	<0.0001	1.44	4.21E+00	<0.0001	1.19	3.26E+00	<0.0001
Program Family	41	437	0.98	2.41E+00	<0.0001	0.11	1.11E+00	0.3959	-6.75	1.20E+03	<0.0001	0.04	9.65E-01	0.6781	1.81	4.12E+00	<0.0001	1.44	4.21E+00	<0.0001	1.19	3.26E+00	<0.0001
Program Family	41	438	-0.12	8.88E-01	0.2732	0.30	1.38E+00	0.0371	0.41	1.51E+00	0.0112	0.12	1.18E+00	0.2739	-0.06	9.48E-01	0.5556	0.18	1.20E+00	0.1371	0.19	1.21E+00	0.1265
Program Family	41	439	-1.11	3.20E+01	<0.0001	-2.06	1.28E+01	<0.0001	0.23	1.25E+00	0.9319	-1.23	2.94E+01	<0.0001	-0.03	9.77E-01	0.7318	-0.93	3.98E+00	<0.0001	-1.05	3.51E+00	<0.0001
Program Family	41	440	0.11	1.11E+00	0.0001	0.11	1.11E+00	0.0001	-0.15	1.15E+00	0.0001	-0.15	1.15E+00	0.0001	-0.03	9.77E-01	0.7318	-0.93	3.98E+00	<0.0001	-1.05	3.51E+00	<0.0001
Program Family	41	441	-1.71	1.82E+01	<0.0001	-3.19	4.13E+02	<0.0001	-40.41	0.00E+00	<0.0001	-10.99	0.00E+00	<0.0001	-11.31	0.00E+00	<0.0001	-17.85	0.00E+00	<0.0001	-16.57	0.00E+00	<0.0001
Activities	42	442	-0.28	7.59E-01	0.0489	-0.09	9.11E-01	0.3589	0.41	1.51E+00	0.0107	-0.06	9.40E-01	0.5954	0.08	1.08E+00	0.4201	0.33	1.39E+00	0.0270	0.39	1.84E+00	0.0407