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An extended Bayesian network approach for analyzing supply chain disruptions

Ivy Elizabeth Donaldson Soberanis
University of Iowa

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AN EXTENDED BAYESIAN NETWORK APPROACH FOR ANALYZING SUPPLY CHAIN DISRUPTIONS

by

Ivy Elizabeth Donaldson Soberanis

<u>An Abstract</u>

Of a thesis submitted in partial fulfillment of the
requirements for the Doctor of Philosophy
degree in Industrial Engineering
in the Graduate College of
The University of Iowa

May 2010

Thesis Supervisor: Professor Peter J. O'Grady

ABSTRACT

Supply chain management (SCM) is the oversight of materials, information, and finances as they move in a process from supplier to manufacturer to wholesaler to retailer to consumer. Supply chain management involves coordinating and integrating these flows both within and among companies as efficiently as possible. The supply chain consists of interconnected components that can be complex and dynamic in nature. Therefore, an interruption in one subnetwork of the system may have an adverse effect on another subnetworks, which will result in a supply chain disruption.

Disruptions from an event or series of events can have costly and widespread ramifications. When a disruption occurs, the speed at which the problem is discovered becomes critical. There is an urgent need for efficient monitoring of the supply chain. By examining the vulnerability of the supply chain network, supply chain managers will be able to mitigate risk and develop quick response strategies in order to reduce supply chain disruption. However, modeling these complex supply chain systems is a challenging research task.

This research is concerned with developing an extended Bayesian Network approach to analyze supply chain disruptions. The aim is to develop strategies that can reduce the adverse effects of the disruptions and hence improve overall system reliability.

The supply chain disruptions is modeled using Bayesian Networks-a method of modeling the cause of current and future events, which has the ability to model the large number of variables in a supply chain and has proven to be a powerful tool under conditions of uncertainty. Two impact factors are defined. These are the Bayesian Impact Factor (BIF) and the Node Failure Impact Factor ($NFIF$).

An industrial example is used to illustrate the application proposed to make the supply chain more reliable. Additionally, two Bayesian Network learning methodology exponential smoothing and neural networks, are examined to update the probabilities in a supply chain disruption model. The neural network seems to be a more promising updating tool. Finally, future research tasks are identified.

Abstract Approved: ______________________________
Thesis Supervisor

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Title and Department

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Date

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Graduate College
The University of Iowa
Iowa City, Iowa

CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

Ivy Elizabeth Donaldson Soberanis

has been approved by the Examining Committee for the thesis requirement for the Doctor of Philosophy degree in Industrial Engineering at the May 2010 graduation.

Thesis Committee:

Peter J. O'Grady, Thesis Supervisor

Yong Chen

Andrew Kusiak

Pavlo Krokhmal

Gerald Schnoor

To
my dear husband,
Policarpio Soberanis,
for his constant support and encouragement

And also to
my parents
Roy and Elaine Parboosingh,
for their endless guidance and motivation throughout my life

Education is not the piling on of learning, information, data, facts, skills, or abilities - that's training or instruction - but is rather making visible what is hidden as a seed.

Thomas More

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ABSTRACT

Supply chain management (SCM) is the oversight of materials, information, and finances as they move in a process from supplier to manufacturer to wholesaler to retailer to consumer. Supply chain management involves coordinating and integrating these flows both within and among companies as efficiently as possible. The supply chain consists of interconnected components that can be complex and dynamic in nature. Therefore, an interruption in one subnetwork of the system may have an adverse effect on another subnetworks, which will result in a supply chain disruption.

Disruptions from an event or series of events can have costly and widespread ramifications. When a disruption occurs, the speed at which the problem is discovered becomes critical. There is an urgent need for efficient monitoring of the supply chain. By examining the vulnerability of the supply chain network, supply chain managers will be able to mitigate risk and develop quick response strategies in order to reduce supply chain disruption. However, modeling these complex supply chain systems is a challenging research task.

This research is concerned with developing an extended Bayesian Network approach to analyze supply chain disruptions. The aim is to develop strategies that can reduce the adverse effects of the disruptions and hence improve overall system reliability.

The supply chain disruptions is modeled using Bayesian Networks-a method of modeling the cause of current and future events, which has the ability to model the large number of variables in a supply chain and has proven to be a powerful tool under conditions of uncertainty. Two impact factors are defined. These are the Bayesian Impact Factor (*BIF*) and the Node Failure Impact Factor (*NFIF*).

An industrial example is used to illustrate the application proposed to make the supply chain more reliable. Additionally, two Bayesian Network learning methodology exponential smoothing and neural networks, are examined to update the probabilities in a supply chain disruption model. The neural network seems to be a more promising updating tool. Finally, future research tasks are identified.

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INTRODUCTION

1.1 Overview

Supply chain disruptions are unplanned and unanticipated events that interrupt the flow of goods and materials or continuity of a supply chain, which can be complex, sizeable and probabilistic in nature. Companies are negatively affected by disruptions regardless of the size. Disruptions from an event or series of events such as the north-east black out in 2003 can have costly and widespread ramifications. Research has been conducted by Kleindorfer and Saad (2005), Craighead et al. (2007), Blackhurst et al. (2005), Wagner and Bode (2007), and Sheffi (2005) to illustrate the high priority supply chain disruptions should be in supply chain management. However, there is still a lot of work to be down in modeling the effects of disruptions on supply chain performance.

Efficiency and robustness are two key aspects of supply chain management. Companies tend to focus more on the efficiency of the supply chain. Efficient companies are not immune to disruptions. In fact, efficient companies may not be as prepared for interruptions in the supply chain due to the steps taken to become more efficient. Companies practice lean supply chains that have minimal slack. Theoretically these companies are efficient when all expectations are met, but are extremely fragile under uncertain conditions. Companies can be left paralyzed when faced with unforeseen occurrences.

For the most part glitches are amplified when undetected (Hendricks and Singhal, 2003). In order to prevent undetected disruptions to be amplified, companies need to respond in a timely fashion. Hendricks and Singhal (2003), suggests that companies need to have an elapsed time of zero between occurrence and detection, which will lessen the severity of the impact. In order to minimize the effect of a disruption, companies need to take into account various situations that could pose a problem, which would assist in being better planners and forecasters of risks, and be more prepared to respond to disruptions. Modeling the disruption in the supply chain with various size and complexity is a challenging research task, but this breakthrough will assist individuals to be better able to determine the effects of the disruptions on supply chain performance.

Recent events have unveiled the inadequacies of the supply chain managers to react quickly and get things up and running speedily. Unless the supply chains are robust and reliable the impact of a disruption will be severe. Supply chain disruption is an important area, as a small disruption caused by a localized event may have a global impact. Due to globalization, outsourcing and offshoring there is no control of causes or consequences of the supply chain. Therefore, it is better to prepare for such event than react when an event takes place.

1.2 Research Objectives

This research is concerned with developing an extended Bayesian Network approach to analyze supply chain disruptions. The aim is to develop strategies that can reduce the adverse effects of the disruptions and hence improve overall system reliability. The supply chain disruptions is modeled using Bayesian Networks-a method of modeling the cause of current and future events, which has the ability to model the large number of variables in a supply chain and has proven to be a powerful tool under conditions of uncertainty.

Two impact factors are defined. These are the Bayesian Impact Factor (BIF)

and the Node Failure Impact Factor (*NFIF*). An industrial example is used to illustrate the application proposed to make the supply chain more reliable, which demonstrates how uncertainties in the supply chain and failure in the node affects the supply chain as well as how changes propagate though the network model. Consequently, supply chain managers are better equipped to make strategic decisions by identifying the probable impact of a failure in the system.

The Bayesian Network facilitates prior knowledge and is useful in determining casual relationships. Moreover, a form of learning can be used. It is imperative to be able to update the probability estimates in the dynamic supply chain. The methodology is to use learning to update probabilities in a supply chain disruption model that can handle the complexity and size of supply chains. With this in mind, two Bayesian Network learning methodology exponential smoothing and neural networks, are examined to update the probabilities in a supply chain disruption model. The neural network seems to be a more promising updating tool. Finally, future research tasks are identified.

1.3 Thesis Proposal Structure

This thesis proposal consists of five chapters. Chapter 1 gives an overview of the research problem and presents the goal of the research. Chapter 2 reviews literature concerning supply chain characteristics and supply chain disruptions and modeling approaches that can be applied to addressing supply chain disruption, an overview of Bayesian Networks and their application to supply chain systems and the Bayesian Network Propagation. Chapter 3 follows with an introduction to each research issue addressed in this research. Chapter 4 presents a Bayesian Network approach for modeling disruption in a supply chain. Chapter 5 compares the effectiveness of using neural networks and exponential smoothing as a probabilistic updating method for updating the Bayesian Networks in the supply chain. Chapter 6 summarizes the conclusions and presents future research tasks. The organization of this thesis proposal is illustrated in Figure 1.1 below.

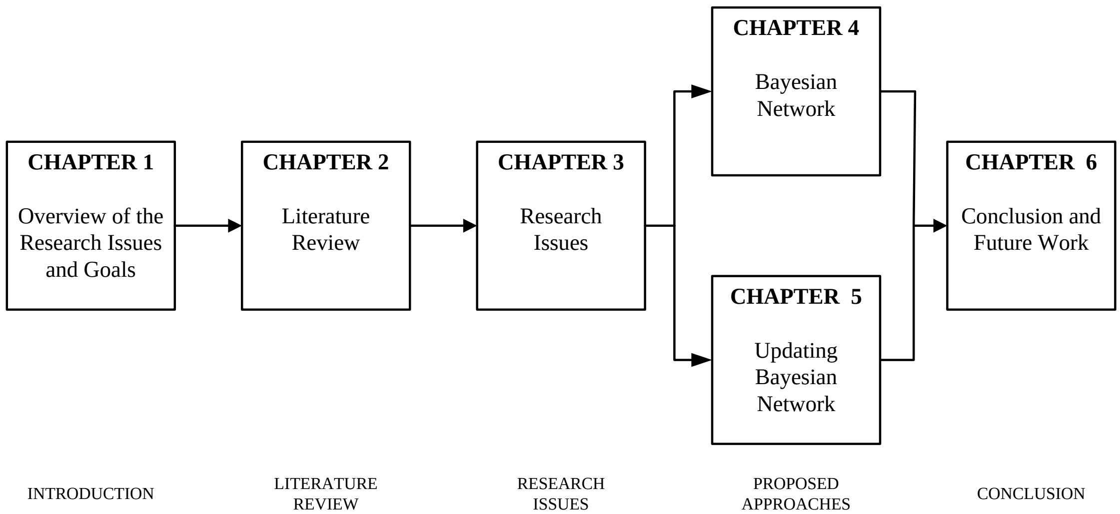


Figure 1.1: Organization of Thesis

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

A supply chain is a network of facilities that procure raw materials, transform them into intermediate goods and then final products, and delivers the products to customers through a distribution system (Lee and Billington, 1995). There has been a significant amount of research in supply chains, much of which has been concerned with ensuring efficient operation under normal operating conditions. Such research is made more challenging due to the inherent size and complexity of many real-world supply chains, combined with their inherent dynamic and stochastic nature.

While there has been significant research in the normal operation of supply chains, the study of the effects of disruptions on the operation of supply chains is now starting to attract attention (Wagner and Bode, 2007; Craighead et al., 2007; Sheffi, 2005; Kleindorfer and Saad, 2005; Blackhurst et al., 2005). Supply chain disruptions are unplanned and unanticipated events that interrupt the flow of goods and materials or continuity of a supply chain. The changes and fluctuation in the demand of customers many cause the supply chain to fail to respond to customers in a timely fashion, which may result in a bottleneck that may have a long term effect on the company (Anupindi and Akella, 1993).

Disruptions from an event or series of events, such as the North East US power blackout in 2003, can have costly and widespread ramifications. For simplicity, a supply chain disruption is the situation that leads to the occurrence of risk; it is not the sole determinant of the final result (Wagner and Bode, 2007). Disruptions to the operation of a supply chain can be a frequent occurrence and can include shortages of materials, demand changes, capacity changes, capacity overloading and human errors (Blackhurst et al., 2007) that can expose firms within the supply chain to operational and financial risks (Craighead et al., 2007). Supply chain disruption can be internal and external. Various events can have a different effect on the supply chain. Wagner and Bode (2007) pointed out that the classification of supply chain disruption can be labeled as supply chain risk sources. Various individuals such as Chopra and Sodhi (2004), Christopher and Peck (2004), Hallikas et al. (2004) and Svensson (2000) have tried to classify supply chain disruptions in the form of typologies (conceptual) and/or taxonomies (empirical) of risks (Wagner and Bode, 2007). For example Svensson (2000) classified disruption into quantitative and qualitative, while Jüttner (2005) identified the source of the risk as supply, demand, and environmental.

Disruptions can have severe adverse effects, as the following example demonstrates. On March 17, 2000, a lightning bolt struck a Philips semiconductor plant in Albuquerque, New Mexico, created a 10-minute blaze that contaminated millions of chips and subsequently delayed deliveries to its two largest customers: Finlands Nokia and Swedens Ericsson. Nokia immediately responded by switching orders to other Phillips plants and other Japanese and American suppliers. However, Ericsson had no other source of microchips and responded late to the disruption. As a result, Ericsson had a shortage in chips and was unable to produce the new generation of cell phones. At the end of the first disruption-impacted quarter, Ericsson reported losses of US $340 million before taxes, which led to a nine-month recovery time. At the end of 2000, Ericsson announced a staggering US $1.68 billion loss in the companys mobile phone division (Latour, 2001; Sheffi, 2000).

Having a backup supplier was very instrumental in Nokia dealing with the disruption in Albuquerque, New Mexico. In general, A supply chain is only as strong as its weakest link (Chidambaram et al., 1999). A failure in one of the links could affect many aspects of the supply network. In fact, the more complex the supply network mean there are more links and potentially a higher risk of failure (Craighead et al., 2007).

The work of Riddalls et al. (2002) shows the costly effects of disruptions including increased lead-times, shortages, reductions in customer service levels, and increases in costs. From the corporate financial perspective, Hendricks and Singhal (2003) show that publicly announced supply chain disruptions can have an adverse effect on market valuation. Their study of 519 announced supply chain problems decreased market capitalization of the companies concerned by an average of 10.28 %. Levy (1995) investigates supply chain disruptions in an international setting and determines that disruptions can result in unexpected costs. The reaction of managers, subjected to supply chain disruptions, tends to be to view the disruption as exceptional rather than as a result of inadequacies in the supply chain design (Levy, 1995).

It is thought that disruptions are amplified when undetected (Hendricks and Singhal, 2003). In order to prevent undetected disruptions to be amplified, companies need to respond in a timely fashion. Hendricks and Singhal (2003), suggests that companies need to have an elapsed time of zero between occurrence and detection, which will lessen the severity of the impact. In order to minimize the effect of a disruption, companies need to take into account various situations that could pose a problem, which would assist in being better planners and forecasters of risks, and be more prepared to respond to disruptions. Modeling the disruption in the supply chain with various size and complexity is a challenging research task, but this breakthrough will assist individuals to be better able to determine the effects of the disruptions on supply chain performance. Researchers such as Tomlin and Snyder (2006) look at how proper planning of a firm may affect the strategies in reducing the impact of a disruption. In fact, the firm may need to adapt and be flexible on a case-by-case basis.

The study of disruptions in supply chains is being driven by four main factors that can amplify the effects of disruptions. The first is the increasing use of lean techniques; where inventory levels are driven lower to increase overall system efficiency. The reduced inventory levels can mean that supply chains are more vulnerable (Sheffi, 2005; Elkins et al., 2005; Jüttner et al., 2003) to disruptions, since there is a reduced safety stock in such lean environments. The second is the rise in global trade, so that parts can be made in different countries and supply chains are increasingly global in nature. Global supply chains can be more susceptible to disruptions in transport or subject to delay at ports. The third is the increasing sophistication of products and the consequent increase in the number of components and the size of the supply chain. The fourth factor is the shortened product cycles where products have to recoup their development costs in a shorter time. Any delays in the supply chain, and the consequent delay in sales, can adversely affect this.

The primary source of risk can be categorized into three categories: operational contingencies, which include equipment malfunctions and systemic failures, abrupt disruption in supply, bankruptcy and other financial distress; natural hazards such as earthquakes, hurricanes, and storms; and terrorism and political instability (Kleindorfer and Saad, 2005). Furthermore, the supply chain disruption severity can be characterized by the density (spacing of nodes within the supply chain), complexity (total number of nodes and flows) and node criticality (importance of a node) (Craighead et al., 2007). According to the risk classification presented by Sheffi (2006) a company is most vulnerable where the disruption probability is high and the consequence of the disruption is severe and is the least vulnerable when there is a low disruption probability and the consequence of the disruption is minimal. Supply chain disruptions can be classified into the three categories of small-scale random disruptions, amplified random disruptions and large-scale major disruptions as described below.

Small-Scale Random Disruptions

Small-scale random disruptions are those that are often endemic to the operation of inventory and supply chain systems, caused by the usual random variations in, for example, customer demand or delivery lead time This category of disruption has received a relatively large amount of attention in the literature and the effects of such disruptions can be reduced by standard approaches such as maintaining increased safety stock or buffer inventories (Chopra and Sodhi, 2004; Kouvelis and Milner, 2002).

Amplified Random Disruptions

Amplified random disruptions are those small-scale disruptions that become amplified and consequently have larger, and more wide-spread, effects. Perhaps the best know example of this category of disruption is the Bullwhip effect, or demand amplification effect, where small changes in demand can be amplified as the effects spread (Riddalls et al., 2002; Shapiro, 2001; Simchi-Levi et al., 2000; Taylor, 2000; Handfield and Nichols, 1999; Suri, 1998; Lee et al., 1997a,b). The main causes of the bullwhip effect include a lack of demand visibility, distortion of information along the chain where individual decision points along the chain creates distorted demand levels and frequent adjustments to inventory levels, which cause erratic order patterns for upstream processes. The effects of amplified random disruptions can therefore be reduced, though not necessarily eliminated, by information sharing and tight coordination (Lee, 2002).

Large-Scale Major Disruptions

Large-scale major disruptions are intense or severe interruptions of the flow or continuity in the supply chain. As such, this category of disruptions tends to occur infrequently but have major effects on the operation of the supply chain.

Events such as hurricane Katrina and the September 11 disaster have increased the perceived business risks for companies. There is mostly anecdotal evidence that companies have been more concerned with short term finances, reducing costs by such initiatives as Just-in-time (JIT) (Bundschuh et al., 2006). As a result, they may have become increasingly dependent upon suppliers and more vulnerable to disruptions. Some companies have also employed global procurement and outsourcing to drive down cost, which results in a network of organizations where companies are linked together.

However, there are certain risks associated with outsourcing. In fact supply chain disruptions can increase significantly with the increase in outsourcing to a particular region. Lynn (2005) points out that companies in the United States are extremely dependent on China. Companies sourcing from China are more likely to experience large scale disruptions due to the poor communication in global supply networks, long lead-times associated with purchases overseas, and the complexity of the distribution channels associated with import regulations and security, multiple transfers, and customs requirements (Craighead et al., 2007). Companies such as Sony realized the potential disruption and inflexibility of the long lines from China and decided to pull their manufacturing out of China and into Japan (Jiang, 2003).

Companies are not immune to the catastrophic impact that a large-scale major disruption can have. Wagner and Bode reported on the response from 760 executives in Germany identified that vulnerability of companies can be attributed to their dependence on customers and suppliers, single sourcing, or reliance on global supply sources risks (Wagner and Bode, 2007). The potential vulnerability of the supply chain makes this issue very important. Companies tend to focus on the consequence of an event along with the likelihood of such an event occurring (Sheffi, 2006).

Research has shown that most organizations are not adequately prepared to manage supply chain risks. Studies suggest that only between 5% and 25% percent of Fortune 500 companies are prepared to handle crises or disruptions (Mitroff and Alpaslan, 2003) and failure to respond quickly to a disruption can be very costly.

Lean manufacturing is very effective under the right condition; however, with a small perturbation in the system the entire system can come to a halt. The complexity and interdependence of nodes in the supply chain makes the supply chain very difficult to analyze. One event may have different degrees of severity in different parts of the supply chain. Therefore, depending on the disruption this may propagate through the network faster in some regions and not so fast in others. In other words the effect is not linear and may be difficult to quantify. Some research has been conducted in order to address supply chain disruption issues. Some researchers have looked into coping strategies to mitigate risks such as inventory (Sheffi, 2005), dual sourcing (Tomlin, 2006) and product mixing Tomlin and Wang (2004).

Just-In-Time Supply chain relies heavily on the transportation system and may result in savings on the part of the company. However, the benefits from adopting JIT inventory principles may be advantageous if there is a right balance of inventory. However, too much or too little inventory could potential be costly. Larson (2005) in an article on UPS Supply Chain Solutions, mentioned that production planning, sourcing and logistics are three very important features of the supply chain that need to be addressed in order to have a cost efficient supply chain.

Supply chain vulnerability is a risk factor that is present in business around the world. In 2005, the fifth largest port in the world, and an important part of the U.S supply chain, was hit by hurricane Katrina. This severed many supply chains. The Louisiana area was not the only area that was affected by this disaster. Particularly hard-hit by the loss of suppliers was the chemical industry, which relies heavily on petroleum-based products. Twelve percent of U.S. refiners capacity was shut down by hurricane Katrina (McCarthy, 2005). The September 11 disaster in New York may not have affected the supply chain as much as hurricane Katrina, due to the fact that New Orleans is more of a manufacturing and marine hub than New York, but it still had a far reaching impact on the supply chain. For example, people were not able to make or receive calls. This no doubt disrupted the communication network and affected the supply chain.

2.2 Mitigating Risks

All supply chains are inherently risky because all supply chain will experience sooner or later one or more unanticipated events that would disrupt normal flow of goods and materials. Therefore, there is an urgency to find ways in which to manage supply chain disruptions. Buffer inventory is one way to deal with an interruption in the supply chain network. However, storing inventory is costly and can be risky.

Uncertainty in customer demand can result in the Bull-Whip effect. Other factors that may contribute to the vulnerability of the supply chain: globalization, reduction in supplier base, and centralized distribution.

A more appropriate strategy to deal with a disruption in the supply network is to design a more robust supply chain. In order for the supply chain to be successful this requires close attention to robust supply chain evaluation tools (Wang et al., 2005). Beamon (1998) points out that performance measures for firms can be divided into qualitative and quantitative measures. Some qualitative measures that one can look for in a supply chain design are customer satisfaction, flexibility, information and material flow, effective risk management and supplier performance. The quantitative measures would be based on cost or profit and customer responsiveness.

In modeling the supply chain there are certain restrictions that needs to be taken into account: capacity, service compliance and extent of demand as well as decision variables, which sets the limit on the range of the outcomes (Min and Zhou, 2002). In essence, the supply chain operates in an uncertain environment (Petrovic et al., 1999). Consequently, determining supply chain performance can prove to be difficult (Huang et al., 2003).

2.3 Research in Supply Chain Disruptions

2.3.1 Network Based Approaches

Network-based approaches use a higher level abstraction of the underlying supply chain in order to remove some of the complexity from the analysis. The basis for the analysis is often an adapted Petri-Net (Zurawski and Zhou, 1994). Petri-Nets use both graphical and mathematic methods to analyze concurrent, asynchronous, distributed, parallel, nondeterministic, and /or stochastic systems (Murata, 1989).

Such characteristics are inherent in many supply chains. Petri-Nets model systems as a series of nodes connected by arcs. The behavior of the system is described by the movement of tokens through the network. A transition nodes is enabled if each of its input place node has at least as many tokens in it as arcs from the place node to the transition node. If the transition node is enabled, and if other conditions are met, the transition node can fire, thereby placing tokens in its output nodes, again subject to some conditions and depending on the type of Petri-Net used. The graphical representation used allows for a ready communication between users, while the mathematical underpinnings of Petri-Nets allow for a formal analysis of the system.

A number of variants of Petri-Nets have been proposed. The family of Petri-Nets has been classified by David and Alla (1994) into the three categories of ordinary Petri-Nets, abbreviations and extensions. Ordinary Petri-Nets have all arcs with a weight of 1, a single token type, infinite capacities in the place nodes, the firing of a token can occur if every place preceding it contains at least one token and no time is involved. Petri-Net abbreviations include generalized Petri-Nets, finite capacity Petri-Nets, and colored Petri-Nets. The extensions to Petri-Nets correspond to models to which functioning rules have been added. Extensions include: inhibitor arc Petri-Nets, priority Petri-Nets, continuous Petri-Nets; hybrid Petri-Nets, synchronized Petri-Nets, timed Petri-Nets; interpreted Petri-Nets, and stochastic Petri-Nets. A colored Petri-Net includes color sets and color functions to allow for additional information to be considered. Wu and Blackhurst (2005) use a Petri Net model to model three levels of a supply chain network: component level, interface level and system level. These are used to model the disruptions in supply chain system. A case study of an aircraft communication equipment manufacturer was conducted.

Li et al. (2006) model the supply chain as a Directed Acyclic Supply Network, which depicts the operations centers, material, and material flow. The disruption material flow is modeled as an Impact Network and the time and cost of a disruption can be ascertained. This model is applied to Haiers supply chain in China. The authors show, as would be expected, that sharing information about disruptions can increase the agility of a company. The network-based approaches used thus far may not be applicable to large-scale systems and the consideration of global supply chain issues remains to be addressed.

2.3.2 Principal-Agent Approaches

The principal-agent model is concerned with a principal contracting with an agent so that the agent performs specific tasks or roles. The contract usually includes a compensation agreement, with the compensation being a function of the agent's output. The agent then takes some actions, usually to positively affect their output, but the principal cannot observe these actions. Events then occur that are beyond the control of the agent. The agent's output is dependent of the actions taken by the agent and by the events that are beyond the control of the agent. An example would be where a house seller (the principal) contracts with a real-estate agent (the agent) to sell the house. The contract specifies the compensation to the agent from selling the house, usually as a percentage of the selling price of the house. The agent then takes some actions to increase the selling price of the house, such as publicizing the house to other real-estate agents. The actual selling price of the house will depend on the actions taken by the agent and by events, such as the economy and interest rates, which are beyond the control of the agent. The agent then receives compensation as specified in the contract. The principal-agent model can be viewed as a balance between insurance and incentives for the agent. An agent has full insurance when they are guaranteed a fixed amount of compensation regardless of the agent's output. An example is where a real-estate agent receives a fixed amount that does not vary with the selling price of the house. Under these circumstances there is little incentive for the agent to improve their output. The converse of full insurance is full incentive, where the agent receives all the output above a fixed level. An example is where a house seller agrees that the agent will receive all the monies from selling the house above a certain level. This is equivalent to selling the house to an agent at a price P for the agent to resell, with the agent thereby retaining all monies from the eventual sale above P.

The ideal contract will usually lie between the extremes of full insurance and full incentives. Research has been done on a number of forms of the principal-agent model. The linear-normal-exponential form assumes a linear output function where the output is a linear combination of the agent's actions and the events beyond the agent's control, the incentive contract is also linear, the agent's objective function is normal and the agent's utility function is exponential. Under these rather limiting circumstances, an optimal linear incentive contract can be determined (Banker and Datar, 1989; Holmstrom, 1979). Holmstrom and Milgrom (1987) extend this to the case of a series of outcomes. However, linear contracts have been shown to be inferior to a number of non-linear contracts (Mirrlees, 1974). For example, a contract that includes step functions can produce full insurance and full incentives at the limit (Mirrlees, 1974).

Non-linear contracts can create incentives that are history-dependent (Oyer, 1998; Chevalier and Ellison, 1997; Brown et al., 1996; Asch, 1990; Healy, 1985) and the form of the compensation agreement can cause gaming and distortions (Kerr, 1975). In particular, using a narrow performance measure as the basis for compensation can cause an agent to concentrate on this measure while neglecting other portions of their task. As an example: “In 1992, Sears abolished the commission plan in its auto-repair shops, which paid mechanics based on the profits from repairs authorized by customers. Mechanics misled customers into authorizing unnecessary repairs, leading California officials to prepare to close Sears auto-repair business statewide” (Baker et al., 1994).

The implication of this is that it appears that great care has to be taken in selecting the performance measure that fully reflects a “good” output measure, from the perspective of the principal. This approach reflects the use of a formal contract that is enforceable.

As an alternative, agents can receive incentive compensation based on subjective assessments by the principal, in what can be termed a relational contract. Such relational contracts have been discussed by Levin (2003), Compte (1998), Kandori and Matsushima (1998), Baker et al. (1994) and Bull (1987). While it may at first appear that relational contracts would have a degree of flexibility that formal contracts lack, they can be surprisingly difficult to change. This may be because many relational contracts are developed over a relatively long period of time. An example is the IBM ”no layoffs” policy in place at IBM for many years. This policy was not a formal contract but was instead a relational contract that was understood by both the firm and the employees. As computer demand moved from large mainframes, the traditional strength of IBM, to the more competitive market for personal computers, IBM moved away from the policy and started to lay off employees, but only at the cost of considerable disquiet in the remaining employees.

While much of the work on principal-agent approaches has concentrated on firm to firm relationships, the work is also applicable to firm-employee relationships where the employment contract can be a mixture of formal and relational contracts with both objective and subjective performance measures. One aspect that is particular to firm-employee relationships is the issue of career concerns, where the employee has an incentive to work hard to influence the firm's perception of their abilities. Holmstrom (1982) examines this issue and shows that inefficiencies can arise where managers can work too hard in their early years in order to cement a good perception of their work while working not hard enough in later years. This "slacking off" can be particularly acute as retirement nears.

The application of principal-agent approaches to supply chain disruption can be considered in a number of scenarios that involve firm-to-firm contracts, including the following:

Sequential where the principal and agents are sequential members of a supply chain. An example is where a product assembler (the principal) contracts with a supplier (the agent). The materials pass sequentially from the supplier to the assembler.

Hierarchical where the principal contracts with product manufacturers and distributors while not actually directly involved in the product manufacture or distribution. An example is the Xbox, where Microsoft (the principal) contracts with product manufacturers and distributors (the agents) without being directly involved in the product manufacturing or distribution (Microsoft, 2002).

In addition, principal-agent approaches can be considered within a firm, where the firm (the principal) contracts with the employees (the agents) to, it is hoped, achieve an efficient operation.

In order to motivate the agent, there may be direct incentives through contracts. There may also be competitions or "tournaments" – where there is pay for performance to motivate agents. Principal-agent models can seem helpful in identifying some issues within an organization and exploring efficient ways to resolve these issues (Sappington, 1991). Incentives between and within firms can be rewarding to all players (Gibbons, 2005). The drawback with giving incentives is that a performance standard needs to be set. "The true test of agency theory is not simply that agents respond to incentives, but that the contracts predicted by the theory are confirmed by observed data" (Prendergast, 1999). The data is subjective, which makes it difficult to evaluate various tasks. Furthermore, it is a difficult task to monitor the agents' activities.

Principal-agent approaches can be useful in examining the operation of a supply chain. Their application to supply chain disruption has had little attention and remains an area of future research.

2.3.3 Behavioral Approaches

Academic papers on supply chain assume that the decision makers are completely rational. However, in some situations one can conclude that decision makers can be irrational. The behavioral biases that are psychological or incentive related can affect the forecast for an inventory policy. The underlying behavioral principles come primarily from psychology, sociology and anthropology. Shiller (1998) elaborated on the various behavioral principles such as prospect theory, regret and cognitive dissonance, mental compartment, overconfidence, over- and under reaction and representativeness heuristic, disjunction effect, gambling behavior and speculation, irrelevance of history, magical thinking, quasi-magical thinking, attention anomalies and the availability heuristic, culture and social contagion and global culture that can affect human behavior in the financial markets, which can be applicable in the supply chain.

Behavioral approach introduces a bias in supply chain decision-making process that may have suboptimal solutions, where decision managers act as irrational agents. We have a limited information processing capacity, which prohibits us from carrying out various tasks at the same time. Take for example a driver in Manhattan, New York who is approaching an intersection. This individual has to pay attention to the traffic light, traffic ahead, pedestrians and oncoming traffic. If being in this situation is not difficult as it is, what if the phone rings? Does he or she answer it? That is a decision that would be made based on his or her cognitive limitations. Likewise, due to the complexity of the supply chain that has various strategic and operational activities, managers are unable to consider every input or variable in making a decision. Therefore, decision makers may only take into account a few inputs in coming up with a decision. As a result, the manager may take shortcuts to deal with supply chain issues. This could lead to the bullwhip effect, where a change in the supply chain becomes exaggerated throughout the supply chain that may have a negative impact on the supply chain. The bullwhip effect describes the phenomena that the variation of demand increases up the supply chain from customer to supplier.

Human's irrational traits cannot be avoided totally and can be totally unpredictable. In order to analyze human behavior in the supply chain process, experiments such as the beer game, surveys from managers, and models are used. The behavioral causes of the bullwhip effect were first tested using the beer distribution game by Sterman (1989) where the oscillation and application of orders were observed, which is referred to as the bullwhip effect. Researches continue to use the beer game to bring forth a certain behavior that is characteristic of most supply chain.

Supply chain inefficiency may be better understood by looking closely at the behavioral side of the equation. This is clearly illustrated in an experiment conducted by Croson and Donohue (2006). Under controlled conditions with no changes in operational demands, the bullwhip effect was still evident even for participants who were trained logistics professionals (Croson and Donohue, 2006). Croson and Donohue (2006) suggested that the bullwhip effect could be attributed to the subjects cognitive limitations. Based on experimental data it appears that the behavioral bias does have an impact on the supply chain oscillations and amplification of orders.

In other experiments in examining the behavioral causes of the bullwhip effect, researchers have concluded that sharing information could to some extent rectify the bullwhip effect that causes disruption in the supply chain. Lee et al. (2000) two-stage supply chain (retailers and manufactures) model shows that information sharing can reduce inventory and increase cost savings. However, experiments conducted have indicated that information sharing and point of sale data will mostly benefit upstream managers (Croson and Donohue, 2006, 2002; Lee et al., 2000, 1997a). Information sharing on inventory levels helps to reduce the bullwhip effect by helping upstream managers in the supply chain to better anticipate and prepare for changes in inventory downstream in the supply chain (Croson and Donohue, 2006). It would appear that it would be more beneficial for retailers to report their inventory position to the manufacturer. In order to reduce the variability upstream in the supply chain this would require tracking and information sharing downstream in the supply chain.

The behavioral approach would require researchers to take all the behavioral biases into account in examining the influence these biases may have on the supply chain inventory and forecasts.

2.3.4 Stochastic Models

2.3.4.1 Stochastic Programming

Stochastic programming is a framework for modeling optimization problems that involves uncertainty (van der Vlerk, 2006), which is modeled through discrete and continuous probability function. These models are applicable to cases where a decision has to be made prior to collecting all the data. Stochastic programming was developed from incorporating uncertainty in linear and other optimization models and has been applied to agricultural economics (Tintner, 1955), scheduling (Dempster, 1982), airline crew scheduling problem (Yen and Birge, 2006), finance (Kouwenberg and Zenios, 2001) and many other areas.

There are various approaches that can be used to solve stochastic programming - programming with recourse, stochastic linear programming, stochastic integer programming, stochastic mixed integer programming, stochastic non-linear programming, and probabilistic programming. For more details of these solution methods please refer to the textbook of Birge and Louveaux (1997) and the paper of Sahinidis (2004).

Stochastic programming is an appropriate tool for solving problems under uncertainty (Maatman et al., 2002; Cocks, 1968). In fact, Maatman et al. (2002); Cocks (1968) showed that the stochastic programming approach is superior to linear programming in looking at the crop-planning problem-profit maximization model of two crops. He pointed out that there are unknown variables that are not available in the planning stage. Therefore decisions had to be made prior to knowing the outcome. This problem was better assessed using stochastic programming instead of linear programming.

The most widely used model in supply chain management is two-stage stochastic programming with recourse, which has been applied to linear, integer and non-linear programming. In the first stage a decision is made to take some action. After the random event occurs a recourse decision is made in the second stage. The first stage variables are chosen so as to minimize the sum of the first stage cost and the expected value of the random second stage cost. In the two-stage model with recourse, stages are used to discretely model time based as information becomes available.

Many individuals have looked at solving uncertainties in supply chain using stochastic programming by examining a two-stage optimization procedure (Birge and Louveaux, 1997). The two-stage approach is improved with the benders decomposition algorithm (Santoso et al., 2003; MirHassani et al., 2000). Performance is usually expressed as a function of the decision variable-location, allocation, network structuring, number of facilities and equipment, number of stages, service sequence, volume, inventory level, size of workforce and the extent of outsourcing. MirHassani et al. (2000) also suggest that the performance of the two-stage stochastic model solution can be improved by introducing the Lagrangean (Barbarosoglu and Ozgur, 1999) method as well as parallel branch and bound. Scenario analysis (Eppen et al., 1989) can be used to provide answers to hypothetical questions that may affect the supply chain and can be used along with two-stage stochastic programming with recourse (MirHassani et al., 2000) to analyze uncertainties in the supply chain. Usually after the first stage, the recourse decision there is a hasty response to the observed scenario that can be costly in contrast to decisions made ahead of time (Shmoys and Swamy, 2006). Shmoys and Swamy (2006) illustrated in an example how the recourse cost may prove to be more expensive in opening additional facilities after opening the initial facility, due to short lead time and difference in resources required for different facilities.

A stochastic programming model is one of the more challenging optimization problems and can be computationally difficult. Stochastic programming models can lead to large-scale problems that can be difficult to manage and solve (Sen, 2001). Shmoys and Swamy (2005) presented an algorithm that works for both discrete and continuous distributions to solve a large class of two-stage stochastic linear programs in polynomial time. This algorithm for two-stage stochastic integer programs algorithm has been applied to multi-commodity flow problems, covering problems, and facility location problems (Shmoys and Swamy, 2006).

Other algorithms have being formulated that can potentially be used for supply chain management uncertainty applications. Stochastic linear programs (SLP) with recourse are widely used in most applications. Despite the fact that SLP problems are convex optimization problems, it lacks smoothness and is differentiable under very special circumstances (Sen, 2001). Shmoys and Swamy (2006) algorithm for solving stochastic linear programming adapted the ellipsoid method to solve a convex-programming relaxation of the problem. The objective function for the stochastic mixed integer linear programs (S-MILP) can be discontinuous. In addition, S-MILP can be cumbersome and computationally difficult (Sen, 2001). This can be dealt with by incorporating the proposed stochastic branch and bound algorithm by Norkin et al. (1998). In addition, the convexity of the recourse function is not guaranteed for mixed-integer recourse models (Stougie and van der Vlerk, 2005).

There has also been work done on multi-stage stochastic linear programming problems with a focus on application with small number of stages (Ariyawansa and Felt, 2004). To address multistage problems, data-aggregation (Frauendorfer, 1994) has been proposed that gives limited computational results. More recently, Shmoys and Swamy (2005) showed that a class of multi-stage stochastic programs could be solved to near-optimality in polynomial time. Despite the progress in deriving solutions using the two-stage model, there is still a lot of work required for multi-stage stochastic programming.

2.3.4.2 Fuzzy Mathematical Programming

Fuzzy mathematical programming is based on Bellman and Zadeh (1970) and further developed by Tanaka et al. (1974) and Zimmermann (1976). Fuzzy mathematical programming addresses optimization problems under uncertainty-vagueness and ambiguity, by means of flexible programming, possibilistic programming (Sahinidis, 2004) and robust programming (Negoita, 1981). Random parameters are considered as fuzzy numbers and constraints are treated as fuzzy sets. In supply chain, uncertainty in customer demand, holding and backorder costs can be modeled through fuzzy sets.

There have been a few studies that have examined uncertainty through fuzzy set theory (Petrovic et al., 1999; Park, 1987). In fuzzy mathematical programming (Figure 2.1), objective functions are treated as constraints that define the decision makers expectations with the lower and upper bounds of these constraints (Sahinidis, 2004).

Stochastic programming is traditionally used as a technique for optimization under uncertainty. In fuzzy programming various solutions can be derived to show the intent of the decision maker. In general, solving a fuzzy mathematical programming problem can be easier to solve than a stochastic programming problem. However, if the uncertain variables are independent then a small number of decision variables take non-zero values in the optimal solution of the fuzzy mathematical programming problem, while the stochastic programming problem, a large number of decision variables takes nonzero values in the optimal solution (Inuiguchi and Ramik, 2000).

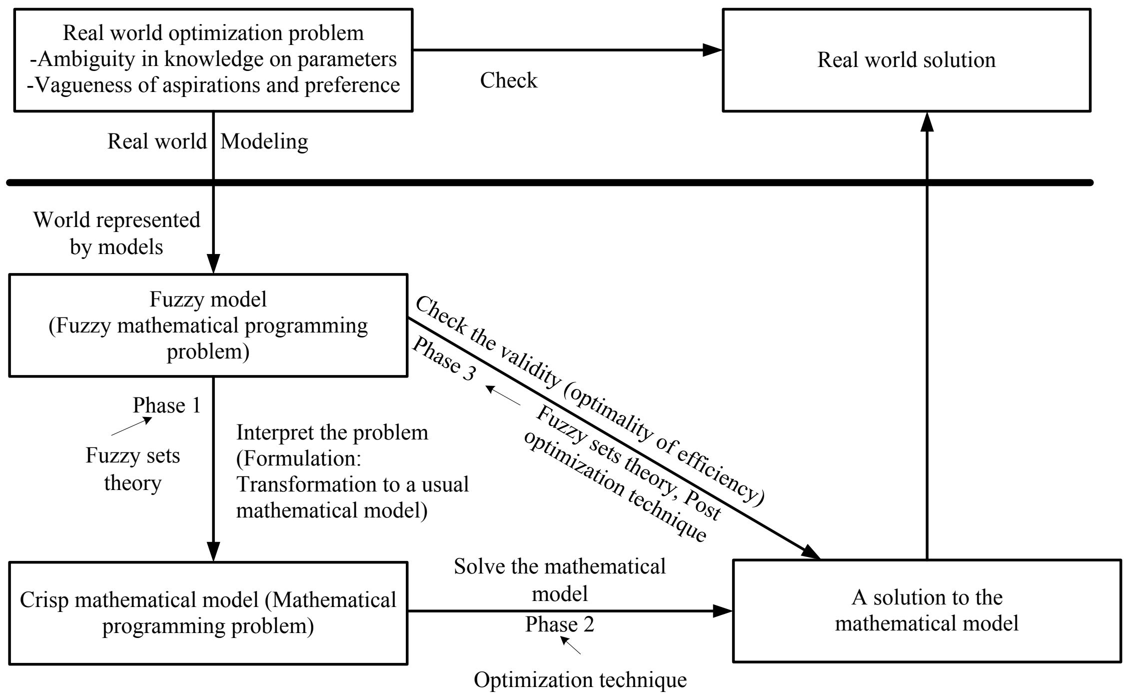


Figure 2.1: Fuzzy mathematical programming approach
(Inuiguchi and Ramik, 2000)

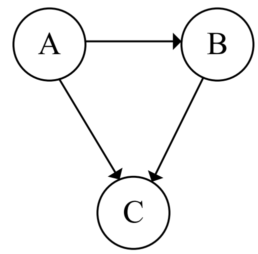
2.3.5 Bayesian Networks

A Bayesian Network is a directed acyclic graph with the nodes representing variables and the arcs represent the conditional dependencies between the variables. Each node of a discrete Bayesian Network has a conditional probability table that lists the probabilities that the child node takes on each of its different values for each combination of values of its parent nodes. Potential advantages of Bayesian Networks compared with other approaches to modeling supply chain disruptions include the compact representation, the robustness to small alterations of the model, the ability to operate with different variable types, the facilitation of prior knowledge, the ability to handle incomplete data sets, and a form of learning can be used.

Bayesian networks (also known as belief networks, probability networks or causal networks) are directed acyclic graphs that consist of nodes and arcs (Figure 2.2) (Ghahramani, 1997). The nodes represent variables, which can be discrete or continuous. The arcs represent causal relationships between the variables (Fenton, 2007). Probability theory is used to deal with uncertainty by the conditional representation of all the components in the networks. Bayesian networks do not depend on various variables. They depend only on the parent or relating neighboring nodes. Bayesian networks are effective models for representing uncertainty using the historical knowledge available and provide a representation for modeling cause and effect. In essence the past is used to predict the future. Bayesian networks use machine-learning techniques that are often used to build user models (Abdelsalam and Ebrahim, 2004).

The Bayesian network can be used to model preferences, habits and uncertain events. Probabilities are calculated based on historical events. For example, in a supply chain network, the system is able to observe what each agent does on a daily basis and assign different probabilities to all the agents in the supply chain. This information can be used to update the probability associated with the agent in the supply chain depending on the disruption in the network. Bayesian networks are being used as an alternative to Artificial Intelligence (AI), map learning (Dean, 1990), language understanding (Charniak and Goldman, 1989), heuristic search (Hansson and Mayer, 1989), medical diagnosis (Heckerman, 1990) and so on. In the supply chain

A: T	A: F
0.40	0.60



A	B: T	B: F
T	0.40	0.60
F	0.01	0.99

A	B	C: T	C: F
T	T	0.99	0.01
T	F	0.90	0.10
F	T	0.80	0.20
F	F	0.00	1.00

Figure 2.2: A Simple Bayesian Network

network there are many uncertainties that confront companies on a daily basis. With this in mind, the Bayesian network can prove to be an effective means of predicting the reliability of the system given disruption in the network.

In 1993, Microsoft began working on Lumiere, now the Office Assistant. The Lumiere is an adaptive Word assistant that is able to predict the users goals and assists the user by learning his or her action sequence (Liu et al., 2003). This software was created to interact with the users by anticipating the individuals needs or goals, which apply the Bayesian networks (Horvitz et al., 1998). Users of computer software are able to get assistance by making queries. However, there are occasions where the navigation system is unable to render assistance due to an unfamiliar query, which may result in frustration.

Despite the many useful attributes of the Bayesian network, there are limitations. In order to calculate the probability of the branch of the network, the probabilities of all the branches are required, which could be difficult to determine. In addition, the reliability and validity of the Bayesian network is based on the reliability of prior knowledge (Niedermayer, 1998).

2.4 Conclusions

This Chapter has reviewed the literature that pertains to the modeling of the effects of disruptions on supply chain operations. First the background to supply chains is discussed, this is followed by a discussion of Network-Based, Principal-Agent, Behavioral, Stochastic Model and Bayesian Network approaches. From the literature on the background to supply chain disruptions, it is evident that supply chain disruptions can be significant in their effects with a substantial impact on the operations of a company and even on their market capitalization. Network-based approaches can model supply chain operations but the research has only applied network-base methods to relatively small problems. The network-based approaches used thus far may not be applicable to large-scale systems and the consideration of global supply chain issues remains to be addressed.

The research on the application of both principal-agent and behavioral approaches to supply chain disruptions has been limited. While the approaches have some applicability to modeling supply chain disruptions, the limited scope of these approaches mean that they can only model part of the system. Stochastic and modeling is a non-deterministic procedure that can be applied to examining supply chain disruptions. The large amount computation required, however, can limit its applicability. While fuzzy mathematical approaches can model some of the less precise operations of a supply chain, the lack of acceptability of fuzzy mathematics may also limit its application.

Bayesian networks offer the potential of modeling supply chain disruptions effectively, particularly the probabilistic nature of much of the operations of a supply chains. However, much research remains to be done into the effectiveness of modeling supply chain disruptions using Bayesian networks. Research needs to be done in examining the application of Bayesian networks to typical supply chains disruptions and in extensions to situations where data may be missing or inaccurate. For example, the absence of historical data, or inaccuracies in the date, may limit the use of Bayesian Neworks since "The Bayesian Network is as useful as the prior knowledge is reliable" (Niedermayer, 1998). Research is therefore needed on learning mechanisms for Bayesian Networks applied to supply chain disruptions.

CHAPTER 3
RESEARCH ISSUES

3.1 Introduction

Chapter Two contains a review of the literature pertaining to analyzing supply chain disruptions. This includes an overview of supply chains and supply chain disruptions and a review of the main approaches to analyzing supply chain disruptions, including Network Based Approaches, Principal-Agent Approaches, Behavioral Approaches, Stochastic Models, Stochastic Programming, Fuzzy Mathematical Programming and Bayesian Networks.

The literature indicates that the effects of supply chain disruptions can be significant, with a substantial impact on the operations of a company and even on their market capitalization. While the approaches reviewed are often limited in their applicability to modeling supply chain disruption, the review indicates that the approach of Bayesian Networks offers the potential of modeling supply chain disruptions effectively, particularly the probabilistic nature of much of the operations of a supply chains. However, also as indicated, much research remains to be done into the effectiveness of modeling supply chain disruptions using Bayesian Networks. The research presented in this thesis proposal is concerned with examining and extending the application of Bayesian Networks to the modeling of the effects of supply chain disruptions.

3.2 Research Issue I: To produce a comprehensive literature review on modeling supply chain disruptions

Currently, there is considerable pressure on companies to improve the operation of supply chains, including making supply chains more robust in responding to disruptions. In a well-designed supply chain, major disruptions would have only a minor and transitory effect, allowing the supply chain to operate efficiently under a wide range of operating conditions. In order to determine the best approaches, it is first necessary to detail the possible characteristics of supply chains, and supply chain disruptions, and to examine the modeling approaches that can be applied to this problem. Consequently, this research issue is:

> *To produce a review of the characteristics of supply chains, and supply chain disruptions, and to examine the modeling approaches that can be applied to this problem.*

3.3 Research Issue II: Modeling supply chain disruptions

Supply chains are often characterized by their complexity, their size and by their inherent probabilistic operation. Given this, modeling supply chain disruptions is therefore a challenging research task. While much research has been carried out in the general area of supply chain management, there appears to have been a relative paucity of reported research in the important area of modeling the effects of disruptions on supply chain performance. The purpose of this research is to examine the modeling of supply chain disruptions using Bayesian Networks, with extensions where necessary. The research issue is:

How can the effects of disruptions in large-scale supply chains be rapidly and effectively modeled and analyzed, particularly in a probabilistic environment?

Modeling the effects of disruptions in large-scale supply chains rapidly and effectively allows users to identify the "weakest link" in the supply chain and be better equipped to plan and forecast for disruptions in the supply chain

3.4 Research Issue III: To use learning to update probabilities for supply chain disruptions

Given the dynamic nature of supply chains, it is important that probability estimates can be updated in a straightforward manner. This would allow a modeling methodology to better determine the effects of disruptions on supply chain performance. As with Research Issue II, the size and complexity of many supply chains means that this is a challenging research task. The resulting research issues are:

To develop a methodology to update probabilities in a supply chain disruption model, that can handle the complexity and size of supply chains.

To illustrate how disruptions in the supply chain propagate throughout the network model.

Updating the probabilities in a supply chain disruption model along with a visual illustration of the propagation of disruptions may assist the user to quickly identify the sub-networks that are affected, as well as the impact of disruptions throughout the interconnected complex supply chain.

3.5 Research Issue Summary

The following chapters in this thesis will discuss these research issues in greater detail. Chapter Four presents a Bayesian network approach for modeling disruption in the supply chain. Chapter Five compares the effectiveness of the exponential smoothing and neural networks as methods for probabilistically updating the Bayesian Network in the supply chain. Chapter Six summarizes the conclusions and presents future research.

CHAPTER 4
BAYESIAN NETWORKS

4.1 Introduction

The research aims to examine modeling the supply chain disruptions using Bayesian Networks. The Bayesian Network facilitates prior knowledge and is useful in determining casual relationships. Moreover, a form of learning can be used.

4.2 Proposed Approach

Supply chain vulnerability is a risk factor that is present in business around the world. Failures can occur for any one of a number of reasons including business failures, strikes, natural disasters, and terrorist incidents. In line with the potential glitches and financial consequences that result from disruptions there is a great urgency to develop ways to manage supply chain disruptions and improve the reliability and robustness of the supply chain.

Supply chain reliability is defined as the probability of the chain meeting mission requirements to provide the required supplies to the critical transfer points within the systems (Thomas, 2002). Many companies have realized the complexity of the supply chain and have taken the necessary steps to enhance the reliability of the supply chain. For example, on May 3, 2006, the Association of American Railroads (AAR) asked that the Federal Energy Regulatory Commission examine the energy supply chain reliability. AAR requested that a workshop be held to examine various issues that may cause problems in the coal supply chain, such as the utility management of coal inventories, ability to meet increasing demand, and unloading capacity at the power plants.

Nomenclature

X	Probability function on the subsets of S, in probability space (S, P)
x	Distinct elements in the sample space
S	Sample space
P	Joint probability distribution of the random variables in the set X
(S, P)	Probability space
$Par(x)$	Parents of node x in S
$P(B)$	Prior or marginal probability of B
$P(A)$	Prior or marginal probability of A, and does not take into account any information about B
$P(B^c)$	Prior or marginal probability of not B
$P(B\|A)$	Conditional probability of B given A
$P(B^c\|A^c)$	Conditional probability of not B not given not A
S_i	Supplier i, where i is the suppliers number $m_i \in M$
M	Place node set $M = (m_1, m_2,)$ in the supply chain network
m_i	Elements of place node set, $m_i \in M$
R_{IFN_i}	The reliability of the Information Flow Network for each node i
RBN_i	The reliability of the Bayesian Network for each node i
R_S	System reliability
S_{IFN}	Information Flow Network of the System
S_{F_i}	Failure in system at node i
P_o	Probability of the system when it is operational

Due to the many factors that may affect the supply chain network, it is a difficult task to pinpoint the exact problem. Consequently, companies may have to re-engineer the supply chain by decreasing lead-times so as to increase the stability of the supply chain (Towill, 1996). Sourcing is another way companies can optimize performance. However, there has to be some level of balance based on the long-term or short-term benefits derived from the selection of suppliers (Childerhouse et al., 2003).

Any consideration of disruptions to supply chains is made difficult by the inherent complexity of many supply chains. The multi-tiered nature of supply chains where each tier has multiple members means that the supply chain can be a complex mesh (Riddalls et al., 2000). In addition, each member can be a member of many other supply chains, each with their own demands and constraints (Sahin and Robinson, 2002). To further add complexity, the Supply Chain may be operating in a dynamic environment, with frequent changes in demand, capacity, suppliers and lead times being the norm. Consequently any study of the effects of disruptions must take this inherent complexity into account. With all these issues in mind, we propose to use the Bayesian Network approach as a means to study supply chain disruptions.

4.2.1 Bayesian Network

Before the introduction of Bayesian networks, probabilistic inference depended on the computation of the conditional probabilities of events from known probabilities using Bayes' theorem.

Theorem 4.2.1 (Baye's Theorem)**.** *Given two events A and B such that $P(A) \neq 0$ and $P(B) \neq 0$ we have*

$$P(A|B) = \frac{P(B|A)P(A)}{P(A)} \tag{4.1}$$

Furthermore, given N mutually exclusive and exhaustive events $A_1, A_2, \cdots, A_N$ and B, such that $P(A_i) \neq 0 \forall i$ and $P(B) \neq 0$. Then, for each $i = 1, 2, \cdots, N$ we have

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{P(B|A_1)P(A_1) + P(B|A_2)P(A_2) + \cdots + P(B|A_N)P(A_N)} \tag{4.2}$$

Using Bayes rule we are able to compute probabilities of an event with the known information we have.

Example 1. *Consider the Bayesian network in Figure 4.1 where A, B and C are random variables. We consider the event A to be the cause of two events B and C and event B to be the cause of event C, where each node has a conditional probability associated. The arrows represent the influence of the A on B and A and B on C. We can use Bayesian theorem (equation 4.2) to calculate the conditional probability of A given C that is $P(A|C)$.*

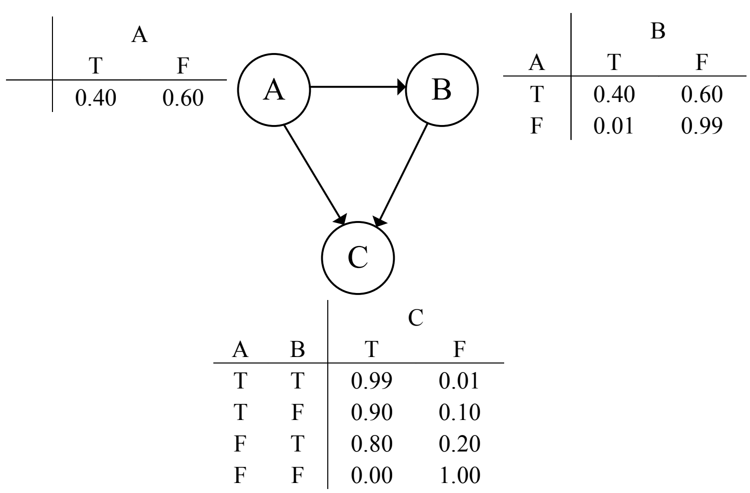


Figure 4.1: A Bayesian Network

$$P(A|C) = \frac{P(C,A)}{P(C)} = \frac{0.00198 + 0.1584}{0.00198 + 0.1584 + 0.288 + 0} = 0.3577$$

Based on the information provided in the probability tables in Figure 4.1, it is 35.77 percent likely that A occurred given C.

In Example 1, Bayes' rule allows unknown probabilities to be computed from known ones. Despite the application of using the Bayesian Theorem, it is limited in the sense that only relatively simple problems can be examined, due to complexity that can arise in the application of this theorem. First we will define the Bayesian network and then give some examples of how we can use the Bayesian network to examine simple to large problems.

Definition 1. *A Bayesian Network (Jensen, 2001) consists of the following:*

1. *A set of variables* $X = \{x_1, x_2, \cdots, x_N\}$ *and a set of directed edges between the variables.*
2. *Each variable has a finite set of mutually exclusive states.*
3. *A directed acyclic graph* S *that is formed from the variables and the directed edges.*
4. *A directed graph is acyclic if there is no directed path* $X = \{x_1, x_2, \cdots, x_N\}$ *s.t.* $x_1 = x_N$.
5. *To each variable* X *with parents* $Par(x_i), \cdots, Par(x_N)$ *there is attached the potential table* $p(X|Par(x_1) \cdots Par(x_N)$.

Taking definition 1 into consideration, we can define the Bayesian network as a probabilistic graphical model that represents a set of variables $X = \{x_1, x_2, \cdots, x_N\}$

and their probabilistic independencies. The graphical structure of the Bayesian network allows the probabilistic relationship to be represented for a large number of variables. The network structure S is a directed acyclic graph (DAG) where the nodes represent variables and the arcs encode conditional independencies between the variables. The nodes in S are one-to-one correspondence (mapping is both one-to-one and onto). For the probability space (S, P), the local probability distribution P is equal to the product of its conditional distributions of all nodes of the graph conditioned on the variables corresponding to the parent of that node in the graph (Heckerman, 1995). In general terms, for a directed acyclic graph of N random variables x the joint probability distribution is given by

$$p(x) = \prod_{i=1}^{N} p(x_i|Par(x_i)) \tag{4.3}$$

where $Par(x_i)$ denotes the states of the parent nodes i and $X = \{x_1, x_2, \cdots, x_N\}$. In the event that node i has no parents, the probability associated with variable x_i is reduced to unconditional probability such that $p(x_i|Par(x_i) = p(x_i)$.

We can expand on the example above (Figure 4.1) to make use of directed graphs to describe probability distributions. Let's consider first an arbitrary joint distribution $p(A, B, C)$ over three variables A, B, and C. We can use the powerful attribute of graphical models that a specific graph can make probabilistic statements for a broad class of distributions. By application of the product rule of probability we can write the joint distribution in the form

$$p(A, B, C) = p(C|A, B)p(A, B) \tag{4.4}$$

We can further break down the right-hand side of equation 4.4 to arrive at equation

4.5, which holds for any choice of the joint distribution:

$$p(A, B, C) = p(C|A, B)p(B|A)p(A) \tag{4.5}$$

Example 2. *Examining the Bayesian network in Figure 4.2, we can extend Example 1 above by considering the joint distribution over N variables given by* $p(x_1, \cdots, x_N)$*. By repeated application of the product rule of probability, this joint distribution can be written as a product of conditional distributions (equation 4.6), one for each of the variables.*

$$p(x_1, \cdots, x_N) = p(x_N|x_1, \cdots, x_{N-1}) \cdots p(x_2|x_1)p(x_1) \tag{4.6}$$

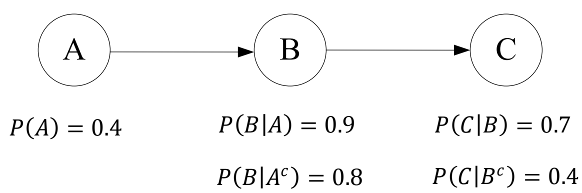


Figure 4.2: A Directed Acyclic Graph (DAG) consisting random variables (nodes) and arcs, with corresponding conditional probability distributions (CPD)

The prior probabilities of all the variables can be computed using the Bayesian Theorem (equation 4.1) above as follows:

$$P(B) = P(B|A)P(A) + P(B|A^c)P(A^c) = (0.9)(0.4) + (0.8)(0.6) = 0.84$$

$$P(C) = P(C|B)P(B) + P(C|B^c)P(B^c) = (0.7)(0.84) + (0.4)(0.16) = 0.652$$

These probabilities can be shown in a network (Figure 4.3). The calculations for variable B and C are calculated using the probabilities of its parent. In this illustration, each node passes on its probability information to its child node in order to compute the probability of the child. This is very useful in calculating the downward propagation of the supply chain network. The upward propagation can be used to calculate the conditional probabilities of other variables. The conditional probabilities that are

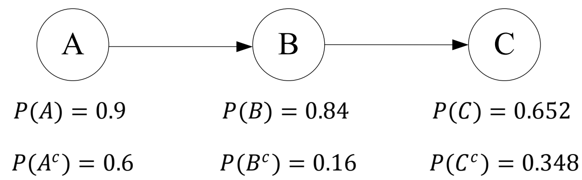


Figure 4.3: A Bayesian network is shown with the probability of the variables in the network

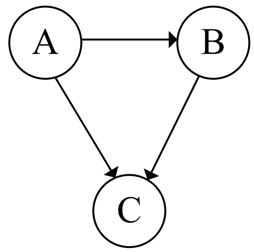
given in the graphical model can be very instrumental in analyzing the network when there is a change at a particular node.

Example 3. *Let us consider the Bayesian network in Figure 4.4. Given a change in one node in the network, we can determine if there are any changes in the network as well as the overall impact on the reliability of the system. Let us assume that P(A) changes from 0.20 to 0.6.*

When the probability of A changes from 0.2 to 0.6, this change is observed throughout the network and in the probability tables associated with the children of that particular node. This is at times referred to as *message passing*. Since A has a direct influence on B and C, the change will have an impact on both random variables B and C. The probability in B changes from .0880 to 0.2440 and the probability of C changes from 0.2379 to 0.6313 (Figure 4.4 and Figure 4.5).

The reliability of the system for this network can be determined using the

	A	
	T	F
	0.20	0.80



	B	
A	T	F
T	0.40	0.60
F	0.01	0.99
E(B)	0.0880	0.9120

		C	
A	B	T	F
T	T	0.99	0.01
T	F	0.90	0.10
F	T	0.80	0.20
F	F	0.00	1.00
E(C)		0.2379	0.7621

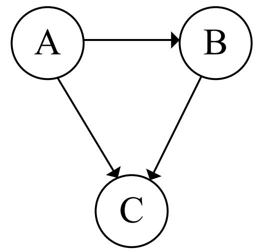
Figure 4.4: A Bayesian network with the conditional probability table of the variables in the network

following formula:

$$R_s = \prod_{i=1}^{N} P_i \tag{4.7}$$

We can use equation 4.7 to determine if there was a change in the reliability of the system from the changes. The reliability of the system increased from 0.0042 to 0.0924. Hence, in this case, the dependence relationship of A on B and C resulted in a more reliable system. Due to the casual relationships, conditional independence allows efficient updating in the network. This link between the nodes and the conditional probability facilitate qualitative and quantitative analysis.

	A	
	T	F
	0.60	0.40



A	B: T	B: F
T	0.40	0.60
F	0.01	0.99
E(B)	0.2440	0.7560

A	B	C: T	C: F
T	T	0.99	0.01
T	F	0.90	0.10
F	T	0.80	0.20
F	F	0.00	1.00
E(C)		0.6313	0.3687

Figure 4.5: A Bayesian network with updated probability tables with a change in A

4.2.2 Bayesian Networks Extension

In a supply chain network, the reliability of each node in the graph is very important in the operational of the supply chain. In addition, the change in each node will have an impact on other nodes in the system as well as the system in general. Therefore, we need to measure the impact that a particular node may have on the network in order to put in place preventative measures that will assist to reduce the effect of a disaster or disruption in the system. To assist with the measurement of the impact of failures or changes in reliability of the nodes in the system, we can extend Bayesian Networks to examine the impact using two impact factors the Bayesian Impact Factor (*BIF*) and the Node Failure Impact Factor (*NFIF*). The algorithms below describe the procedure to attain these values.

Let

R_{IFN} = The reliability of the Information Flow Network for each node i

R_{BN_i}= The reliability of the Bayesian Network for each node i

$R_{S_{IFN}}$= The reliability of the Information Flow Network of the system

$R_{S_{F_i}}$ = The reliability of the system when node i fails

P_o = The probability or reliability constant that the system is operational

Algorithm Bayesian Impact Factor (*BIF*)

Input: A non-empty list of reliability of each node in the Bayesian Network

Output: The Bayesian Impact Factor Negative, Positive or No change

For each node i in the list,

Calculate the Bayesian Impact Factor (BIF) for node i, $\frac{R_{BN_i}}{R_{IFN}}$

IF the $BIF < 1$, THEN

Display NEGATIVE CHANGE

ELSE IF the $BIF = 1$, THEN

Display NO CHANGE

ELSE

Display POSITIVE CHANGE

END IF

The Bayesian Impact Factor (BIF) is a ratio that examines the change in the reliability of the nodes in the system. However, this does not give a clear picture of how the system may be impacted with a severe disruption in a particular node. In fact, there could be failures in more than one node at any given time; however, in the following algorithm to find the Node Failure Impact Factor, only one node failure is taken into account in the analysis of the system reliability.

Algorithm Node-Failure Impact Factor (*NFIF*)

Input: Reliability of the system for each failed node i

Output: Operational Status of system: Operational or Non-operational

Calculate Node failure impact factor (*NFIF*) for each node i, $\frac{R_{S_{F_i}}}{R_{S_{IFN}}}$

IF $NFIF < P_o$, THEN

Display Non-OPERATIONAL,

ELSE

Display OPERATIONAL

END IF

From these algorithms, the node that has the greatest impact on the system in case of a disruption can be ascertained by looking at the factor with the smallest value for both the BIF and $NFIF$. In fact, the Node Failure Impact Factor ($NFIF$) can be sorted in order to see the next largest system failure for a failure of a node. Example 4 below illustrates how these factors can be used.

4.3 Bayesian Networks and Supply Chain Disruption

Example 4. *We will now analyze a partial Metal Fabrication network using the Bayesian Impact Factor and the Node Failure Impact Factor. Blackhurst et al. (2007) describe a case study that involves the supply chain of three parts– Part A: Non Conductive Washer, Part B: Mounting Frame and Part C: Spacer. These parts are manufactured in a metal fabrication shop at Rockwell Collins, Cedar Rapids, Iowa. To aid in understanding the problem of disruption, this section will examine the potential for supply chain disruption for the supply chain for only two parts: Part A: Non*

Conductive Washer and Part B: Mounting Frame. Again, as an aid in understanding the problem, the supply chain is modified for this study to include only the main material flow of the two parts (Figure 4.6). The supply chain includes two main paths (Part A: Non Conductive Washer and Part B: Mounting Frame, that include nodes $m_{25} - m_{30}$ *and nodes* $m_1 - m_{18}$ *respectively). These two main paths converge at node* m_{19} *and the parts then pass through nodes* m_{19} *to* m_{24}*. The supply chain studied in this paper ends at* m_{24}*.*

This study is concerned with examining the potential for disruptions to the supply chain that last longer than one week. Such a lengthy disruption would cause major delivery and supply issues throughout the supply chain. In the supply chain studied, there are various disruptions that can result in the failure of the system. Considering specifically the material flow, how a previous (up-stream) node directly affects the node that is connected by the arc further down the supply chain. A disruption to the upstream node has the potential to directly affect the downstream node. However, there are issues that may be beyond the material flow that may affect the manufacture of a part. These include transport, weather and power disruptions. A recent example is the considerable flooding of Cedar Rapids in summer 2008 that disrupted transport and storage and also disrupted employee attendance for this supply chain. In any study of supply chain disruption, it is important to include these other potential disruptions. Consequently, this work also examines failures due to disruptions outside the realm of the material flow in the supply chain network.

4.3.1 Operation of the Core Supply Chain

The core supply chain consists of the main material flow for the two parts studied (Figure 4.6). As indicated above, the reliability of a node is the probability of a disruption lasting more than one week with a year long horizon. The data for the reliability of each node is taken to be as shown in Table 4.1.Some nodes have alternative parallel nodes and so the effects of a failure of one of the parallel nodes can be minimized. For example, m_5, m_6 and m_7 are alternative parallel operations and a disruption to one node is mitigated by the other two nodes. Other nodes have no alternative parallel nodes and the failure of the node may adversely affect the operation of the whole system. Given the data for the reliability of each node as shown in Table 4.1 the resulting reliability of the system is calculated to be 0.906 when there is no probability of an event. This is calculated using the usual assumption of independence between nodes.

4.4 Supply Chain Augmented with Bayesian Network Analysis

The overall system reliability of 0.905, as calculated above, is an encouraging figure for the overall reliability of the system. However, the analysis used to obtain this figure is narrow and probably erroneous, with potentially dire consequences for the company operations. Errors in the analysis are likely to occur in the central assumption of node independence. In practice, nodes are likely to have some, at least partial, co-dependence in their reliabilities. For example, nodes that are co-located are prone to the same major disruption such as an earthquake or hurricane. Ignoring this interdependence of probabilities can give overly optimistic reliabilities for the whole supply chain.

In this study, the effects of an external event on the system reliability are studied. External events that may impact this particular supply chain include major fires, tornados or floods. Nodes that are co-located are potentially prone to interdependence of reliability and this study examines the potential effects of the co-location of nodes plastic adhesive (m_{28}), CNC brake (m_{17}), standard brake (m_{18}), chemical filmed (m_{19}), rubber stamp (m_{20}) and laser (m_{21}). This study considers an external event, such as a flood, major fire or tornado, on the supply chain resulting in an augmented supply chain, as shown in Figure 4.7. This shows the external event impacting the co-located nodes and the resulting Bayesian network tables for each directly affected node.

It can be seen that the effect of the external event can be a significant reduction in overall system reliability (Table 4.1). With $p(E) = 0$, the system reliability of 0.906 corresponds to that of the core system but with $p(E)$ of 0.01 the system reliability drops to 0.888. The system reliability decreases from 0.725 to 0.035 when the likehood of an event E increases from 0.2 to 0.7.

Given the inclusion of $p(E)$, there becomes a need to significantly increase the reliability of the system. In this study, further analysis is carried out for this augmented network, including detecting nodes that could potentially cause a disruption in the system by using the Node Failure Impact Factor and the Bayesian Impact Factor. The results of this analysis can then be used to make changes to the augmented system to increase overall system reliability.

4.4.1 Node Failure Impact Factor (*NFIF*)

Node Failure Impact Factor (*NFIF*) indicates the effects that unreliable individual nodes have on the overall system. Low values of *NFIF* indicate a large impact on overall system reliability. The results for the augmented system are as shown in Table 4.2 with $p(E)$ of 0, 0.1, 0.2, 0.5 and 1.0 respectively. As can be seen from examining the values of $NFIF$, the system is particularly susceptible to failures in nodes that do not have alternative nodes-m_1, m_4, m_8, m_9, m_{19}, m_{22}, m_{23}, m_{24}, m_{25}, m_{28}, m_{29}, and m_{30} (Figure 4.8), whereas the system is more robust to failures in nodes with alternative operations (m_2, m_3, m_5, m_6, m_7, m_{13}, m_{14}, m_{15}, m_{17}, m_{18}, m_{20}, m_{21}, m_{26}, or m_{27}). The effect of increasing values of $p(E)$ are, as expected to decrease values of *NFIF*, indicating a larger effect on overall system reliability.

4.4.2 Bayesian Impact Factor (*BIF*)

The Bayesian Impact Factor (*BIF*) indicates the impact that changes in the reliability of a node have on the overall system, with lower values indicating increased impact. The results of a *BIF* analysis of the augmented system are shown in Table 4.3 .This shows that nodes m_{17}, m_{18}, m_{19}, m_{20}, m_{21}, and m_{28} have the lowest resulting ratio, which would indicate that these nodes indicate a larger change in reliability of the system (Figure 4.8). Therefore, it is desirable to look at this segment of the supply chain with these particular nodes, since some nodes may have a greater impact than others.

From Table 4.2 failure in m_{17}, m_{18}, m_{20}, or m_{21}, does not result in a failure in the system, while failure in m_{19} and m_{28} resulted in a total failure of the system. The *NFIF* and *BIF* analysis would therefore indicate that nodes m_{19} and m_{28} have the greatest need for improvement. Improvements could include introducing a parallel node or some other redundancy.

4.4.3 Supply Chain Echelons

Another perspective on the reliability of the supply chain can be brought to bear by considering the different echelons of the chain. Echelons refer to the levels in the supply chain so that, in Figure 4.7, one echelon is formed by m_1 and another by m_2, m_3. The levels in the network are labeled as echelon k_i, where $i = 1, \cdots, 18$ (Figure 4.7). The reliabilities of each echelon with differing values of $p(E)$ are shown in Table 4.4. As would be expected, the reliabilities of the affected echelons declines with increasing values of $p(E)$. With $p(E) = 0.4$, for example, the reliability of echelon k_9 drops to 0.609 from 0.997, while the reliability echelon k_{16} drops to 0.608 from 0.990. These echelons have the lowest reliabilities, particularly at high values of $p(E)$ and the results suggest that any remedial attention should focus on echelons k_9 and k_{16} with nodes m_{19} and m_{28} respectively.

4.5 Improving Supply Chain Reliability

Echelons k_9 and k_{16} consist of single nodes with no redundancy. Therefore, one way of improving the reliability of this supply chain is by introducing parallel nodes in these echelons (Figure 4.9). If such an arrangement was to be implemented for echelons k_9 and k_{16}, the effects on supply chain reliability can be dramatic, as shown in Table 4.5. Before the addition of a parallel node, the supply chain had a reliability of 0.549 for $p(E) = 0.2$. However, with parallel nodes, the reliability of the supply chain increased by 55.4% to a reliability of 0.853.

These parallel nodes need not be physically active at all times but could be nodes that can be activated at short notice to replace a failed node. An example would be where an outside party is contracted to provide emergency capacity at relatively short notice. The use of an external agency has the advantage that the node would be physically remote from the original node and hence the effects of $p(E)$ would not be as severe. We can further improve the system by removing nodes from a vulnerable area. In this example, m_{17}, m_{18}, m_{20} and m_{21} are all in this critical area, where m_{17} and m_{20} are parallel to m_{18} and m_{21}. Therefore, in our final implementation we removed m_{18} and m_{21}. With this final step, the reliability of the network is much improved. In fact, the reliability of the system approaches 0.90 for $p(E)$ between 0 and 1 (Table 4.6, Figure 4.10). The resulting supply chain, Figure 4.9, and the network is shown to be more reliable as the probability of an event E occurring (Table 4.7).

4.6 Conclusions

This Chapter has examined the application of Bayesian Networks to supply chains. The basis of Bayes Theorem and the development of Bayesian Networks are described. Since the effects of disruptions on a supply chain needs to be measured, two impact factors are defined. These are the Bayesian Impact Factor (*BIF*) and the Node Failure Impact Factor (*NFIF*). An industrial example is used to illustrate the application of the proposed approach to improving the reliability of supply chains. In this example, the supply chain was examined using Bayesian Networks and, by using measurements of *BIF* and *NFIF*, selective improvements were made in the structure of the supply chain. The result was a considerable improvement in the reliability of the supply chain. There is a huge increase in the reliability of the network, which is clearly shown in Figure 4.10. For example, when the probability of an event is 0.4, the system had a reliability of 26%. However, after all the changes have been implemented the reliability increased to 90%. Consequently, this analysis can have a much improved design of a network.

Nodes	Reliability of the Nodes in the Bayesian Network												
	0	0.01	0.02	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
m_1	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975
m_2	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
m_3	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995	0.995
m_4	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
m_5	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990
m_6	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990
m_7	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981
m_8	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
m_9	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
m_{13}	0.985	0.985	0.985	0.985	0.985	0.985	0.985	0.985	0.985	0.985	0.985	0.985	0.985
m_{14}	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988
m_{15}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
m_{17}	0.986	0.977	0.967	0.893	0.799	0.706	0.613	0.520	0.426	0.333	0.240	0.146	0.053
m_{18}	0.989	0.979	0.970	0.893	0.797	0.701	0.605	0.510	0.414	0.318	0.222	0.126	0.030
m_{19}	0.997	0.987	0.977	0.900	0.803	0.706	0.609	0.512	0.415	0.319	0.222	0.125	0.028
m_{20}	0.988	0.980	0.971	0.905	0.822	0.740	0.657	0.574	0.491	0.408	0.326	0.243	0.160
m_{21}	0.984	0.977	0.969	0.911	0.837	0.764	0.690	0.617	0.544	0.470	0.397	0.323	0.250
m_{22}	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
m_{23}	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989
m_{24}	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994
m_{25}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
m_{26}	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990	0.990
m_{27}	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.988
m_{28}	0.990	0.980	0.971	0.895	0.799	0.704	0.608	0.513	0.418	0.322	0.227	0.131	0.036
m_{29}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
m_{30}	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
System	0.906	0.888	0.870	0.725	0.549	0.391	0.258	0.154	0.081	0.035	0.011	0.002	0.000

Table 4.1: Impact on the nodes in the network with various probability of event E

		Node Failure Impact Factor (*NFIF*)				
	P(E)	0	0.1	0.2	0.5	1
FAILURE OF NODE	m_1	0	0	0	0	0
	m_2	0.995	0.796	0.603	0.17	0.00003
	m_3	0.997	0.798	0.604	0.17	0.00003
	m_4	0	0	0	0	0
	m_5	1	0.8	0.606	0.17	0.00003
	m_6	1	0.8	0.606	0.17	0.00003
	m_7	1	0.8	0.606	0.17	0.00003
	m_8	0	0	0	0	0
	m_9	0	0	0	0	0
	m_{13}	1	0.8	0.606	0.17	0.00003
	m_{14}	1	0.8	0.606	0.17	0.00003
	m_{15}	1	0.8	0.606	0.17	0.00003
	m_{17}	0.989	0.723	0.504	0.114	0.00001
	m_{18}	0.986	0.722	0.505	0.116	0.00002
	m_{19}	0	0	0	0	0
	m_{20}	0.984	0.735	0.523	0.126	0.00002
	m_{21}	0.988	0.73	0.513	0.117	0.00001
	m_{22}	0	0	0	0	0
	m_{23}	0	0	0	0	0
	m_{24}	0	0	0	0	0
	m_{25}	0	0	0	0	0
	m_{26}	0.988	0.79	0.599	0.168	0.00003
	m_{27}	0.99	0.792	0.6	0.169	0.00003
	m_{28}	0	0	0	0	0
	m_{29}	0	0	0	0	0
	m_{30}	0	0	0	0	0
System		1	0.8	0.758	0.281	0.00018

Table 4.2: The Node Failure Impact Factor (*NFIF*) with the failure of each node in the network

Node	Bayesian Impact Factor (*BIF*)					
	0.01	0.1	0.2	0.5	0.8	1
m_1	1	1	1	1	1	1
m_2	1	1	1	1	1	1
m_3	1	1	1	1	1	1
m_4	1	1	1	1	1	1
m_5	1	1	1	1	1	1
m_6	1	1	1	1	1	1
m_7	1	1	1	1	1	1
m_8	1	1	1	1	1	1
m_9	1	1	1	1	1	1
m_{13}	1	1	1	1	1	1
m_{14}	1	1	1	1	1	1
m_{15}	1	1	1	1	1	1
m_{17}	0.991	0.905	0.811	0.527	0.243	0.054
m_{18}	0.99	0.903	0.806	0.515	0.224	0.03
m_{19}	0.99	0.903	0.806	0.514	0.222	0.028
m_{20}	0.992	0.916	0.832	0.581	0.33	0.162
m_{21}	0.993	0.925	0.851	0.627	0.403	0.254
m_{22}	1	1	1	1	1	1
m_{23}	1	1	1	1	1	1
m_{24}	1	1	1	1	1	1
m_{25}	1	1	1	1	1	1
m_{26}	1	1	1	1	1	1
m_{27}	1	1	1	1	1	1
m_{28}	0.99	0.904	0.807	0.518	0.229	0.036
m_{29}	1	1	1	1	1	1
m_{30}	1	1	1	1	1	1
System	0.98	0.8	0.606	0.17	0.012	0

Table 4.3: The Bayesian Impact Factor (BIF) of the nodes in the Network with various P(E)

Echelon	Reliability of the Echelons in the Bayesian Network												
	0	0.01	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
k_1	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975
k_2	1	1	1	1	1	1	1	1	1	1	1	1	1
k_3	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
k_4	1	1	1	1	1	1	1	1	1	1	1	1	1
k_5	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
k_6	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
k_7	1	1	1	1	1	1	1	1	1	1	1	1	1
k_8	1	1	0.999	0.989	0.959	0.912	0.847	0.764	0.664	0.545	0.408	0.254	0.081
k_9	0.997	0.987	0.977	0.9	0.803	0.706	0.609	0.512	0.415	0.319	0.222	0.125	0.028
k_{10}	1	1	0.999	0.992	0.971	0.938	0.894	0.837	0.768	0.687	0.593	0.488	0.37
k_{11}	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
k_{12}	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989
k_{13}	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994
k_{14}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
k_{15}	1	1	1	1	1	1	1	1	1	1	1	1	1
k_{16}	0.99	0.98	0.971	0.895	0.799	0.704	0.608	0.513	0.418	0.322	0.227	0.131	0.036
k_{17}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
k_{18}	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
System	0.906	0.888	0.87	0.725	0.549	0.391	0.258	0.154	0.081	0.035	0.011	0.002	0

Table 4.4: Reliability of the echelons k_i, $i = 1, \cdots, 18$ in the Bayesian Network under various like hood of an event E

Echelon	Reliability of the Echelons in the Bayesian Network with the addition of parallel nodes at k_9 and k_{16}												
	0	0.01	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
k_1	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975
k_2	1	1	1	1	1	1	1	1	1	1	1	1	1
k_3	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
k_4	1	1	1	1	1	1	1	1	1	1	1	1	1
k_5	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
k_6	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
k_7	1	1	1	1	1	1	1	1	1	1	1	1	1
k_8	1	1	0.999	0.989	0.959	0.912	0.847	0.764	0.664	0.545	0.408	0.254	0.081
k_9	1	1	1	1	0.999	0.999	0.999	0.998	0.998	0.998	0.997	0.997	0.997
k_{10}	1	1	0.999	0.992	0.971	0.938	0.894	0.837	0.768	0.687	0.593	0.488	0.37
k_{11}	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
k_{12}	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989
k_{13}	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994
k_{14}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
k_{15}	1	1	1	1	1	1	1	1	1	1	1	1	1
k_{16}	1	1	1	0.999	0.998	0.997	0.996	0.995	0.994	0.993	0.992	0.991	0.99
k_{17}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
k_{18}	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
System	0.918	0.917	0.916	0.899	0.853	0.783	0.692	0.584	0.464	0.34	0.22	0.112	0.027

Table 4.5: The impact on the echelons in the network after the addition of parallel nodes to echelons k_9 and k_{16} with various $p(E)$

Echelon	Reliability of the Echelons in the Bayesian Network with the addition of parallel node to k_9 and k_{16} and removal of vulnerable nodes from k_8 and k_{10}												
	0	0.01	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
k_1	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975	0.975
k_2	1	1	1	1	1	1	1	1	1	1	1	1	1
k_3	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
k_4	1	1	1	1	1	1	1	1	1	1	1	1	1
k_5	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
k_6	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997	0.997
k_7	1	1	1	1	1	1	1	1	1	1	1	1	1
k_8	1	1	1	0.999	0.998	0.997	0.996	0.995	0.994	0.993	0.992	0.991	0.99
k_9	1	1	1	1	0.999	0.999	0.999	0.998	0.998	0.998	0.997	0.997	0.997
k_{10}	1	1	1	0.998	0.997	0.996	0.995	0.993	0.992	0.991	0.989	0.988	0.987
k_{11}	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
k_{12}	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989	0.989
k_{13}	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994	0.994
k_{14}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
k_{15}	1	1	1	1	1	1	1	1	1	1	1	1	1
k_{16}	1	1	1	0.999	0.998	0.997	0.996	0.995	0.994	0.993	0.992	0.991	0.99
k_{17}	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987	0.987
k_{18}	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996
System	0.918	0.918	0.917	0.915	0.911	0.908	0.905	0.901	0.898	0.895	0.892	0.888	0.885

Table 4.6: The impact on the echelons in the network after the addition of parallel nodes to echelon k_9 and k_{16} and the removal of nodes vulnerable to event E from echelon k_8 and k_{10}

Probability of an event E	Reliability of the Network		
	Initial	**Intermediate**	**Final**
	Bayesian Network	Addition of nodes m_{19r} and m_{28r}	Removal of nodes m_{18} and m_{21}
0	0.906	0.918	0.918
0.01	0.888	0.917	0.918
0.05	0.870	0.916	0.917
0.1	0.725	0.899	0.915
0.2	0.549	0.853	0.911
0.3	0.391	0.783	0.908
0.4	0.258	0.692	0.905
0.5	0.154	0.584	0.901
0.6	0.081	0.464	0.898
0.7	0.035	0.340	0.895
0.8	0.011	0.220	0.892
0.9	0.002	0.112	0.888
1.0	0	0.027	0.885

Table 4.7: Network incremental improvement after adding parallel nodes and removing nodes in the bayesian network from the collocated areas that may be affected by an event E

E	m_{17} T	m_{17} F
T	0.05	0.95
F	0.99	0.01

E	m_{20} T	m_{20} F
T	0.16	0.84
F	0.99	0.01

E	m_{18} T	m_{18} F
T	0.03	0.97
F	0.99	0.01

E	m_{21} T	m_{21} F
T	0.25	0.75
F	0.98	0.02

E	m_{19} T	m_{19} F
T	0.03	0.97
F	1.00	0.00

E	m_{28} T	m_{28} F
T	0.04	0.96
F	0.99	0.01

Table 4.8: Conditional Probability of collocated stations where $P(E) = 0$

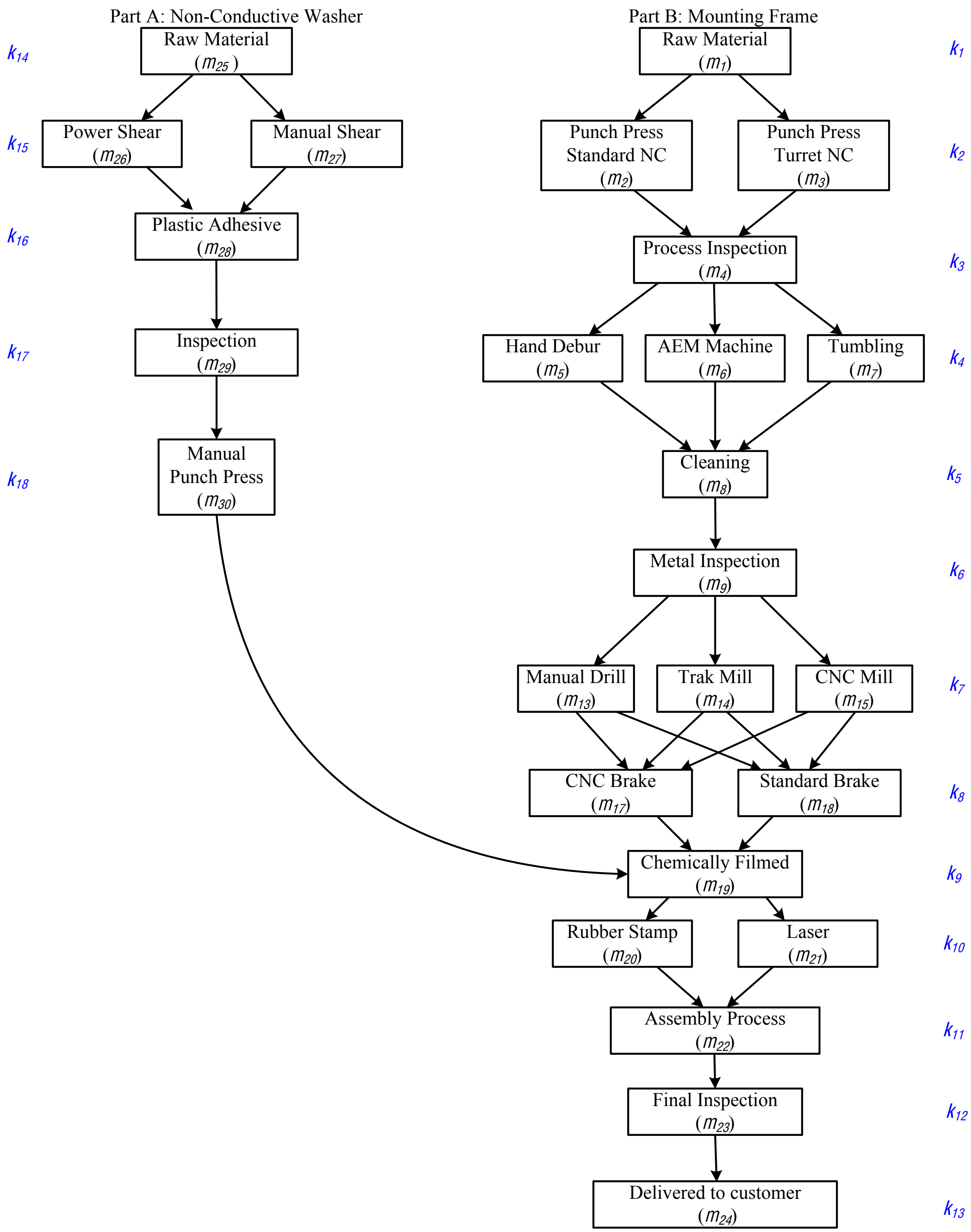


Figure 4.6: Supply Chain Material Flow for Part A: Non-Conductive Washer and Part B: Mounting Frame with k_i echelon levels, where $i = 1, \cdots, 18$

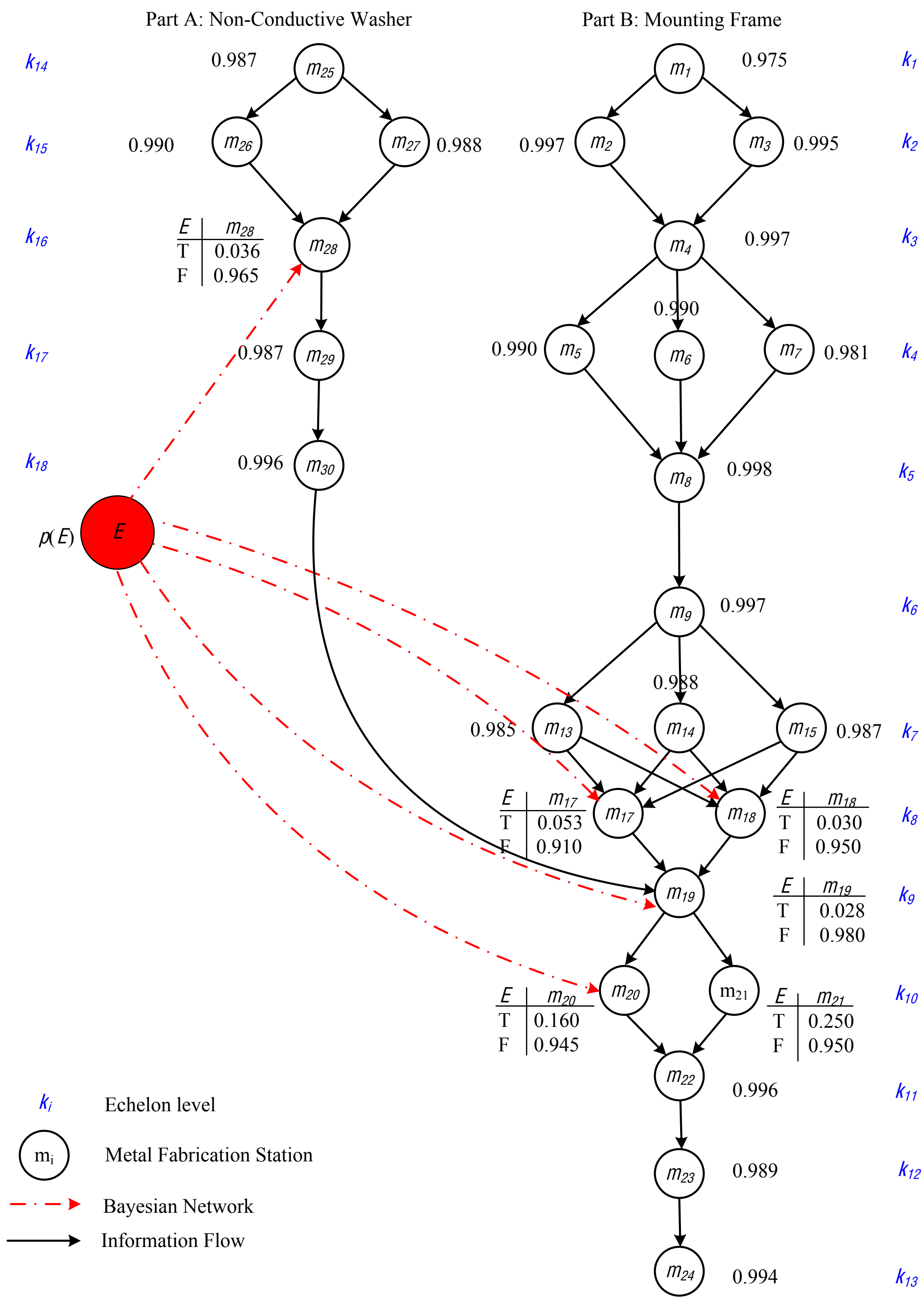


Figure 4.7: Bayesian Network of an event E effect on the collocated stations in the Metal Fabrication network

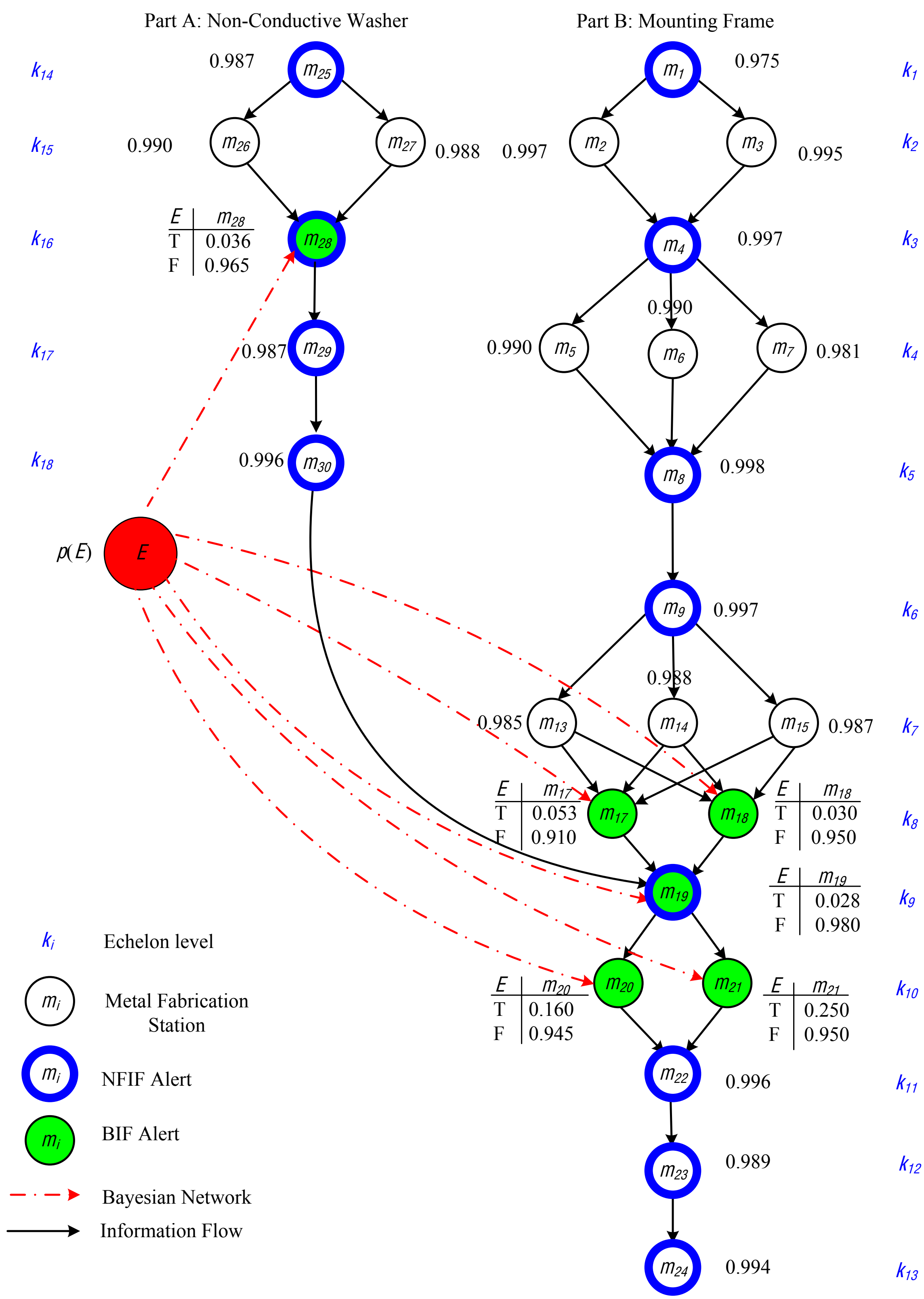


Figure 4.8: The Bayesian Network with the Node Failure Impact Factor ($NFIF$) and the Bayesian Impact Factor (BIF)

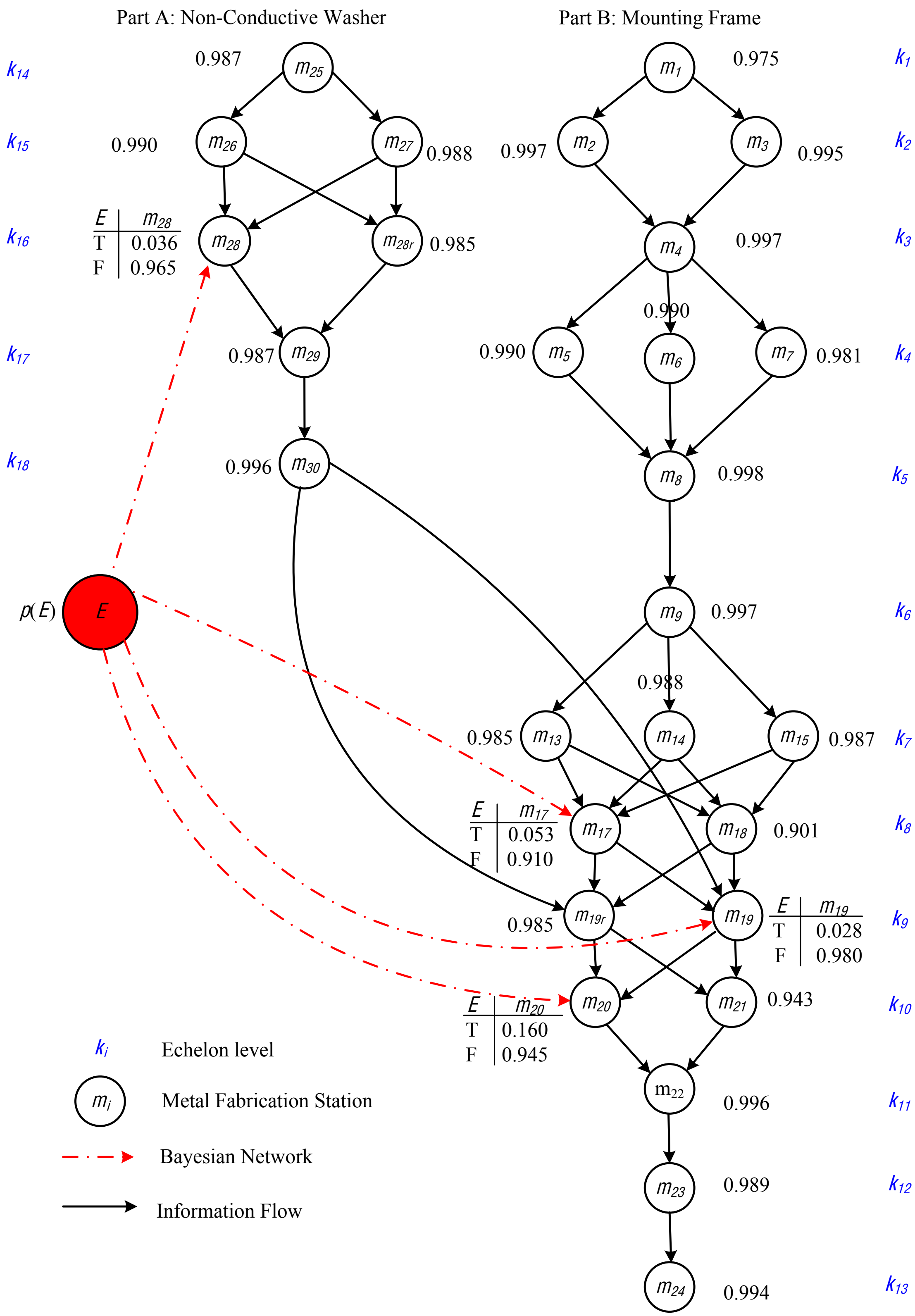


Figure 4.9: Updated Bayesian Network

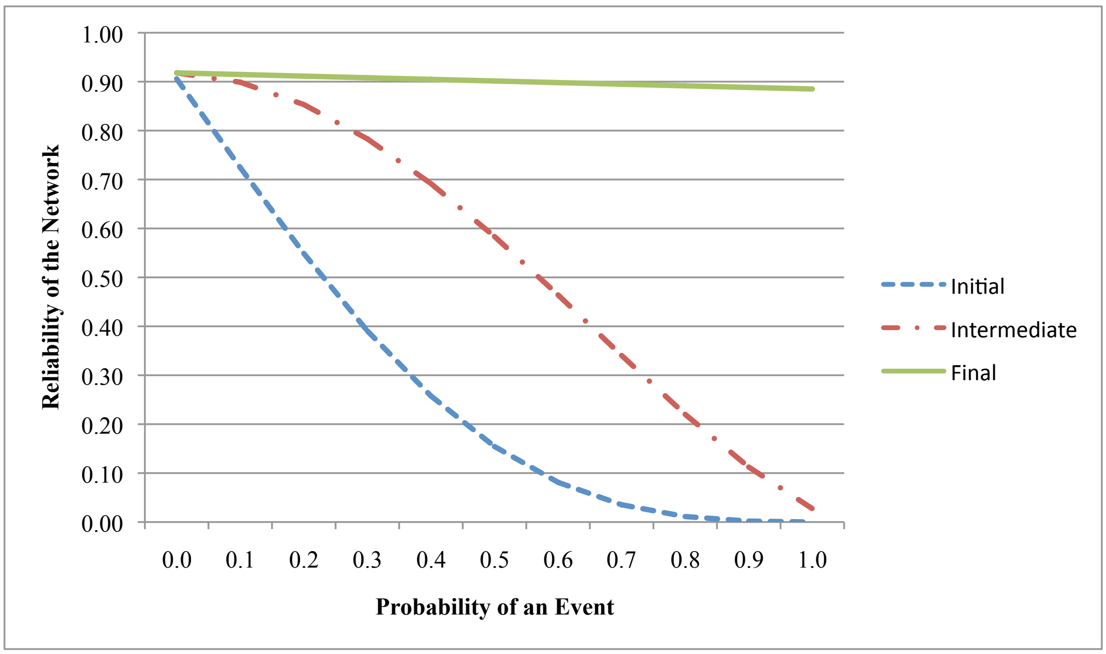


Figure 4.10: Progressive improvements of the network as changes are implemented

CHAPTER 5
BAYESIAN NETWORK LEARNING

5.1 Introduction

Bayesian network learning is a probabilistic approach to building models, which combines prior knowledge with learning from data. The Bayesian network can be very complex and can prove to be a difficult task to define the network. Therefore learning the structure of the Bayesian network is very important. We would like to use prior knowledge and data to update the probabilities in the network structure. The methodology is to use learning to update probabilities in a supply chain disruption model that can handle the complexity and size of supply chains. Future research tasks include analysis to illustrate how changes propagate through the supply chain and how a change affects the other nodes in the supply chain. Examining what change can cause a disruption in a large-scale industry and illustrate this disruption or node impact graphically is of utmost importance in resolving an issue effectively and efficiently.

5.2 Literature Review

The joint probability table increases exponentially with an increase in variables. Therefore, it is important to have an efficient updating algorithm that is applied to the Bayesian networks (Jensen and Nielsen, 2007). Bayesian updating can be computationally complex or NP hard (Cooper, 1990). Bayesian updating can be done using various exact and approximate inference algorithms. The efficiency of the analysis is based on the algorithm used. Different algorithms are more suited for different network structures and performance requirements. In fact, there are occasions where approximate inference algorithms are used over exact inference that becomes computationally infeasible. The exact inference works for limited types of networks with special structure and conditional probabilities in the model (Sun and Chung, 2007). The most popular exact algorithm is the Junction tree algorithm (D'Ambrosio, 1993; Henrion, 1986). There are different kinds of updating used in Bayesian network. In this section the various approaches used will be discussed-message passing, sequential passing, recursive bayesian network updating and junction tree.

5.2.1 Message Passing

Pearl (1988) developed a message-passing algorithm for exact inference in singly connected networks. The algorithm can compute the conditional probability of any variable given any set of evidence by propagation of beliefs between neighboring nodes. A brief overview of message passing can be found in chapter 5 of Pearl (1988). In an extension of the message passing approach to updating the Bayesian Network, Sun and Chung (2007) presented the hybrid message passing approach which the applied to a Bayesian Network that maybe continuous and discrete.

5.2.2 Sequential Passing

In sequential update of Bayesian Networks the learning procedure receives the data as stream of observations and there is an output model from the learning procedure, based on the data observed thus far (Friedman and Goldszmidt, 1998). There are various Sequential Update approaches: naive approach, maximum a-posteriori probability (MAP), and the incremental approaches (Friedman and Goldszmidt, 1998; Lam and Bacchus, 1994; Spiegelhalter and Lauritzen, 1990). In the naive approach all the previous data is stored and can use all the information provided. This makes the naive approach an optimal approach (Friedman and Goldszmidt, 1998). However, the huge amount of data requires a lot of memory. In order to deal with the large data set issue, the MAP approach stores all the previous data by summarizing the data used in the model so far assuming that that the data being summarized has a probability distribution based on the current model. However, using the current model, which uses a summary of past data leads to a bias in the learning process in the model. As a result the model will eventually not change after a while since it will stop adapting to new data. The incremental approach incorporates the strengths of the nave approach and the MAP approach. The incremental approach tries to find good models by using information or data necessary to take the next step in finding a network. The data is updated and stored upon arrival.

5.2.3 Recursive Bayesian Network Updating

Bayesian updating can be recursively and incrementally updated. The wonderful thing about recursive bayesian updating is that it is simple and has a wide variety of applications (Pearl, 1988). In order to calculate the probability hypothesis, the sequence of the old data $\mathbf{e}_n = e^1, e^2, \cdots, e^n$ and the new data e are used. Computing $P(H|\mathbf{e}_n, e)$ can be very complex with the addition of new data. When new data e is added to the sequence of old data the entire data set becomes $\mathbf{e}_{n+1} = \{\mathbf{e}_n, e\}$. Taking this approach when a new data is added would imply that the previous old data would have to be kept for future computation. This would increase the set e, which would not be economical. The idea behind using the recursive network data is to be able to get rid of past data once $P(H|\mathbf{e}_n)$ is calculated. Therefore, the new impact of the new data can be computed by $P(H|\mathbf{e}_n, e)$ once $P(H|\mathbf{e}_n)$ has been computed.

In computing the new impact the old impact $P(H|\mathbf{e}_n)$ is now the prior probability. The old impact is multiplied by the likehood function that measures the probability of the new data given the hypothesis and the past data. The likehood function is also independent of the past data, which makes it a bit simpler to update the new impact.

To get a simple recursive procedure for updating the posterior odds $O(H|\mathbf{e}_n)$, $P(H|\mathbf{e}_n, e)$ is divided by the complementary equation for $\neg H$, which gives the following equation

$$O(H|\mathbf{e}_{n+1}) = O(H|\mathbf{e}_n)L(e|H)$$

However, to simplify this further, we can take the logarithm of $O(H|\mathbf{e}_n)$, which results in the log odds

$$\log O(H|\mathbf{e}_n, e) = \log O(H|\mathbf{e}_n) + \log L(e|H)$$

where the log of the likehood ratio can be viewed as a weight, carried by the evidence, where a favorable hypothesis has a positive weight and an unfavorable hypothesis has a negative weight. The advantage of the log odds notation is that it can be computed efficiently.

An additional benefit of using this method is that the beliefs can be revised. Therefore, in the event there is an error, this can be easily rectified by calculating the change Δ in the initial value e and the new value e'.

$$\Delta = \log L(e'|H) - \log L(e|H)$$

The Δ is then added to the accumulated log-odds $\log O(H|\mathbf{e}_n, e)$. The recursive updating technique depends on the conditional independence relation and will only be applicable when the knowledge of H (or $\neg H$) renders past information as irrelevant with regards to future observation Pearl (1998). If the hypothesis influences the observations only indirectly via causal links then the recursive updating method cannot be applied. Therefore, the influence has to be conditionally independent with no indirect influence.

5.2.4 Junction Tree

The junction tree algorithm provides a methodical and efficient method of clustering. This method involves performing bayesian propagation on an updated graph called a junction tree. The Junction tree (Korb and Nicholson, 2003) approach eliminates cycles in a network by clustering them into single nodes (Lauritzen and Spiegelhalter, 1988). The Junction Tree Algorithm (Hugin algorithm) can be summarized in six steps (for more details refer to Korb and Nicholson (2003) text):

1. Moralize the graph: A directed graph is converted into an undirected graph, so a uniform treatment of directed and undirected graphs is possible. Linking the parents of each node and dropping the directionality of the edges in directed graph obtain the moral graph.

2. Triangulate the graph: Add arcs so that every cycle of length ¿3 has a chord, so that there is a sub cycle composed of exactly three nodes.

3. Create New Structure-the junction tree: Construct a junction tree from this (form a maximal spanning tree)

4. Create separators

5. Compute new parameters

6. Propagate the probabilities (via belief propagation): Evidence is added and propagated using message passing algorithm.

5.3 Updating

Reasoning with Bayesian network is done by updating the probabilities, which involves using new information or evidence to compute the posterior probability distributions. Bayesian updating for any probabilistic inference is the computation of the posterior probability distribution for a set of query nodes, given values for some evidence nodes (Korb and Nicholson, 2003). In the Bayesian Network the value that is observed is conditioned on some observation. The process of conditioning or Bayesian updating or inference is performed via a flow of information through the network (Korb and Nicholson, 2003).

According to Katsuno and Mendelson (1991) update consists in bringing the knowledge base up to date when the world is described by its changes. With this in mind, the input should not only be modeled based on mere observations. In our analysis of the network we need to take into account that we live in a dynamic world where there exists some correlation between each variable/node at different time in the network.

Companies in a supply chain conduct product forecasting for its production scheduling, capacity planning, inventory control, and material requirements planning. Forecasting is a major determinant of inventory costs, service levels, scheduling and staffing efficiency, and many other measures of operational performance Lee et al. (1992). Forecasting in supply chains can be useful in reducing costs and improving performance Zhao et al. (2002).

In the supply chain, information flows upstream to the manager when an order is placed with the supplier. With each order the manager needs to readjust his or her forecast to avoid the bullwhip effect. Companies need to know how much they need to order from a supplier. Forecast errors can contribute to the bullwhip effect, the tendency of orders to increase in variability as one moves up a supply chain (Dejonckheere et al., 2004; Zhang, 2004). Consequently, a forecast of demand is necessary to figure out how much to order. A closer look at the outcome of the beer game can be attributed to the behavioral factors such as the players' perceptions and mistrust. An important factor is each player thought process in projecting the demand pattern based on what he or she observes.

Based on the need for predicting the outcome, demand and behavior, researchers have utilized exponential smoothing for predicting or forecasting in various fields such as finance (Lai et al., 2006) and manufacturing (Kleindorfer and Saad, 2005; Fildes and Beard, 1992; Adshead and Price, 1987). Consequently, the exponential smoothing method has the potential to be used to update the probability of the Bayesian network in the supply chain.

5.3.1 Bayesian Network Propagation

Bayesian network (Pearl, 1988) is a very graphical model that can be used to make probabilistic inference to update and revise belief values (Niedermayer, 1998) and is able to readily permit qualitative inferences without the computational inefficiencies of traditional joint probability determinations and support complex inference modeling. Inference over a factor graph can be done using a message-passing algorithm such as belief propagation, which is more efficient than summing over every variable in the network. Inference problems like marginalization and maximization are NP-hard to solve exactly and approximately (at least for relative error) in a graphical model.

Belief propagation algorithms are normally presented as messages update equations on a factor graph, involving messages between variable nodes and their neighboring factor nodes and vice versa. Considering messages between regions in a graph is one way of generalizing the belief propagation algorithm. There are several ways of defining the set of regions in a graph that can exchange messages. Various researches have been carried out on designing and implementing algorithms for performing inference (Huang and Darwiche, 1996), for instance, the renowned global propagation (GP) method (Jensen et al., 1990; Lauritzen and Spiegelhalter, 1988), path propagation (Wu and He, 2007) and survey propagation.

Survey propagation has proven to be very efficient in NP-complete problems such as graph coloring and satisfiability (Braunstein et al., 2005). The Bayesian network and the global propagation (GP) method for inference have been widely used on applications for small and medium size applications. However, it is rather challenging to use GP method for large Bayesian networks in general. The size of all the cliques in the junction tree is directly related to the efficiency and effectiveness of the Global propagation method. Therefore with the increase in the Bayesian network the junction tree will also increase which will affect the performance of the inference on the now larger Bayesian network and it will take a longer time to perform the global propagation. Furthermore, the Global propagation method involves the inward and outward message passing, which may result in the availability of the probability of all the variables once the Global probability is finished. However, the user may not be interested in all the variables in the network. In fact, the user may only be interested in a few variables, which would mean that the computation performed was not economically advantageous to the user.

With this in mind, Wu and He (2007) developed an on-demand thrifty propagation method called path propagation (PP). This method is modeled on how the Bayesian network is used in practice. The path propagation is based on the assumption that the GP method is applied in full scale only once on a junction tree with no evidence observed, and the marginal for cliques and separators in the tree are known from then on. Based on the experimental results presented by Wu and He (2007), the path propagation method is more efficient and effective in finding a path in the tree. As a result it will also take less time and resources to compute the answer for a query for large and complex Bayesian networks that would otherwise fail to be efficient and effective for the global propagation.

5.4 Learning

Learning can be assisted by the use of existing knowledge, which we can refer to as the training data. In fact, prior knowledge can be enormously useful in learning. The knowledge that we compile or is given can greatly aid in the speeding up the decision making process. There are a variety of learning techniques that can be utilized based on the data. The learning method can be supervised, unsupervised or reinforced.

Supervised learning is the adjustment of the state of the network in response to the data generated in the environment Anthony and Bartlett (1999). In supervised training, both the inputs and the outputs are provided. By means of inductive learning the function must be derived from the input and outputs. Learning a discrete-valued function is called *classification* and learning a continuous function is called *regression*. Some supervised leaning methods are SVMs, neural nets, logistic regression, naive bayes, memory-based learning, random forests, decision trees, bagged trees, boosted trees, and boosted stumps. For a detailed comparison of these ten supervised learning methods, see Caruana and Niculescu-Mizil (2006).

In *unsupervised training*, the network is provided with inputs but not with desired outputs, that is the training data is provided and the likely or unlikely data is derived. The system itself must then decide what features it will use to group the input data or the network has to make sense of the inputs without outside help. There is a cluster of similar data or highly correlated features into similarity groupings. There is no teacher or feedback as to the correct classification (Gallant, 1993). The unsupervised learning principles are crucial for the efficiency (Hrycej, 1992). With unsupervised learning it is possible to predict future states, which makes it possible to evaluate alternative actions and plan several steps ahead. This learning method is very applicable in real-world situations where all the information is not provided. This is often referred to as *self-organization* or *adaptation* (Hrycej, 1992).

Reinforcement learning involves learning decision-making policies for agents (Kaelbling et al., 1996). Reinforcement learning is a combination of supervised and unsupervised learning, where the information is provided in a supervised fashion and the learning algorithm uses this information to make the best decision. Quite a bit of reinforcement learning algorithm has been developed in learning automata (Narendra and Thathachar, 1989), which have been adapted for neural networks. Although the reinforcement learning have well-understood convergence properties, the restricted information can have a negative impact on the quality of the solutions and the speed of convergence (Hrycej, 1992). Therefore it is better to use supervised learning algorithms with the availability of complete information.

5.5 Bayesian Network Learning

Bayesian learning can be reduced to probabilistic inference. Given the learning data, the probability of each hypothesis is calculated and the predictions are made using all the hypotheses, weighted by their probabilities, rather than by using just a the best hypothesis (Russell and Norvig, 2003). However, the data can be complete or incomplete which makes it difficult to use just one learning approach for all training data. We will examine Bayesian learning with both complete and incomplete data.

5.5.1 Bayesian Learning with Complete Data

Existing approaches that are commonly used to learn Bayesian Network structures from data are the *search and scoring* and the *dependency analysis* (Cheng et al., 1997). In the *search and scoring* approach the algorithms that are used to search for a structure that fits the data the best. The search and scoring approach begins with a graph without any edges and add edges to the graph as the search is done. The common scoring function is the posterior probability of the network structure. A scoring method such as the Bayesian scoring method (Heckerman et al., 1995; Cooper and Herskovits, 1992), entropy based method (Herskovits, 1991) and minimum message length method (Wallace et. al., 1996) is employed to check if the current structure is better than the previous one. This process is done until the new structure is better than the old one. The search can be conducted locally or globally. The local search approach makes incremental changes aimed at improving the score of the structure while the global search algorithm such as the Markov Chain Monte Carlo can avoid getting trapped in local minima.

In general, solving the Bayesian network is NP-hard (Chickering et al., 1994). Therefore, a heuristic search such as the greedy local search, best-first search and the

Monte-Carlo techniques are used to solve NP-hard problems (Heckerman et al., 1995; Cooper and Herskovits, 1992). Some search and scoring methods that are used are Chow-Lui Tree Construction Algorithm (Chow and Liu, 1968), Suzuki's Algorithm (Suzuki, 1996), Friedman-Goldszmidt Algorithm (Friedman and Goldszmidt, 1996) and Wallace, Korb and Dai (WKD) (Wallace et al., 1996). The search and scoring approach may not find the best structure but it works better with a wider range of probabilistic models.

In some cases there might be various ways to represent the data. That is a single solution may not be a true representation. Therefore, instead of searching for a single best solution, algorithms (Buntine, 1994) are used to return several networks and the average of these networks are taken to perform the Bayesian network propagation. This method is called the *model averaging technique*.

In the *dependency approach*, the algorithm such as the Boundary DAG Algorithm (Pearl, 1988), Spirtes, Glymour and Scheines (SGS) Algorithm (Spirtes et al., 1990) and Bayesian Network (BN) PowerConstructor (Cheng et al., 1997) tries to find the structure of the network by looking at the dependency relationship from the data. The dependencies are measured by the CI tests. The dependency approach can prove to be useful for sparse networks; however, the CI tests with large condition-sets may be unreliable for small volume of data (Cooper and Herskovits, 1992).

In the approaches discussed above we assume that the data set contains all the variables. However, there are situations where the data is incomplete, where some variables that are being examined are not assigned values. The data could have missing values where some variables are unobserved or hidden variables where the variables are never observed or might not even exist. In these instances there are different algorithms that can be applied to derive the structure of the Bayesian network.

5.5.2 Bayesian Learning with Incomplete Data

Many real-problems have hidden variables that are not observable in the learning data used. Incomplete data or missing data can be handled by using the exact algorithm found in Cooper (1995). Missing values can be handled by well-known Expectation-Maximization (EM) algorithm (Binder et al., 1997; Thiesson, 1995; Lauritzen, 1995), which solves problems in a general way consists of two steps - expectation and maximization (Heckerman, 1995; Dempster et al., 1977) and the Gibbs sampling method (Candidate method), which is applicable when the joint distribution is not known explicitly, but the conditional distribution of each variable is known. The Gibbs sampling method approximation can be extremely accurate and may take a while to converge (Heckerman, 1995). Therefore, for large samples it is very inefficient to use the Monte-Carlo methods. A more appropriate and efficient method to apply for large samples is the Gaussian approximation. Another algorithm specifically designed to be applied to Bayesian network parameter estimation from incomplete data is Bound and Collapse (BC) (Ramoni and Sebastiani, 1997). Bound and Collapse seems to work for particular missing data mechanisms, but unfortunately it is not guaranteed to return valid results for ignorable missing data mechanisms in general (Riggelsen, 2006). In the event that there are hidden data, neural networks can be very useful in learning parameters from noisy data has many applications.

5.6 Extended Bayesian Network Approach

In the Bayesian network the nodes represent random variable and the arcs represent direct influence. For each node in the network there is a conditional probability distribution (CPD) for the corresponding variable given its parents. Bayesian Network can be used to model probabilistic representation of uncertainty. In the Bayesian Networks the probabilities can be updated for each random variable in the network. Therefore, based on new evidence or information that is introduced in the system this information propagates upwards and downwards throughout the system. This bi-directional propagation was first proposed by Pearl (1988) and can be used to update the probability tables. We will look closely at the exponential smoothing and the neural network approach to update probabilities.

5.6.1 Exponential Smoothing

Companies in a supply chain conduct product forecasting for its production scheduling, capacity planning, inventory control, and material requirements planning. Forecasting is a major determinant of inventory costs, service levels, scheduling and staffing efficiency, and many other measures of operational performance (Lee et al., 1992). Forecasting in supply chains can be useful in reducing costs and improving performance(Zhao et al., 2002). In the supply chain, information flows upstream to the manager when an order is placed with the supplier. With each order the manager needs to readjust his or her forecast to avoid the bullwhip effect. Companies need to know how much they need to order from a supplier. Forecast errors can contribute to the bullwhip effect, the tendency of orders to increase in variability as one moves up a supply chain (Dejonckheere et al., 2004; Zhang, 2004). Consequently, a forecast of demand is necessary to figure out how much to order. A closer look at the outcome of the beer game can be attributed to the behavioral factors such as the players' perceptions and mistrust, where each player projects the demand pattern based on what he or she observes. Based on the need for predicting the outcome, demand and behavior, researchers have utilized exponential smoothing for predicting or forecasting in various fields such as finance (Lai et al., 2006) and manufacturing (Fildes and Beard, 1992; Adshead and Price, 1987). However, exponential smoothing has not been used to update the probability of the Bayesian network in the supply chain.

Exponential Smoothing is a technique that is used to produce a smoothed Time Series and is beneficial in forecasting situations. Exponential Smoothing assigns exponentially decreasing weights as the observation get older. This means that more recent observations are given relatively more weight in forecasting than observations that are further in the past. Double Exponential Smoothing is better at handling trends. Triple Exponential Smoothing is better at handling parabola trends. An exponentially weighted moving average with a smoothing constant α, corresponds roughly to a simple moving average of length (i.e., period) n, while the holt-Winters method has 3 updating equations that each has a constant that range from 0 to 1.

Exponential Smoothing is often used on Large Scale Statistical Forecasting problems, because it is both robust and easy to apply. Exponential Smoothing (Gardner, 1985) uses a weighted average of past and current values, adjusting weight on current values to account for the effects of changes in the data. Using an alpha term (between 0-1), which is also referred to as the smoothing coefficient, smoothing factor or smoothing constant, which is determined by the analyst.

The forecast for the next period is calculated by the weighted combination of the last observation A_t and the last forecast $B_t : B_{t+1} = \alpha A_t + (1 - \alpha) B_t$. The smoothed value ($B_{t+1}$) of the data average is the basis for forecasting, which is calculate for each period using the data for that (the current) period and the smoothed value for the previous period.

Nomenclature

α	Smoothing coefficient
A_t	Last observation or datum for now
B_t	Old smoothing value
B_{t+1}	New smoothing value
x	Summation over all the incoming neurons
I_1	State of the node
w	Weight of the connection
n	Number of incoming neurons
T	Threshold
$f(x)$	The activation function
S	Output
TH	Threshold
LR	Learning rate
W	Weights
C	Calculated output
X	Sum of the calculated output (C)
Z	Desired output
N	Network (if $S > TH, 1, 0$)
E	Error $(S - N)$
R	Correction $(LR \times E)$

For forecasting for many periods

$B_{t+1} = \alpha A_t + (1 - \alpha)B_t$

For time t-1:

$B_t = \alpha A_t + (1 - \alpha)B_{t-1}$

Substituting the expression for B_t into equation B_{t+1}

$B_{t+1} = \alpha A_t + (1 - \alpha)(\alpha A_t + (1 - \alpha)B_{t-1})$

which simplifies to

$B_{t+1} = \alpha A_t + \alpha(1 - \alpha)A_{t-1} + (1 - \alpha)2B_{t-1}$

General expression:

$$B_{t+1} = \sum_{n=0}^{\infty} \alpha(1 - \alpha)^n A_{t-n} \tag{5.1}$$

Example 5. *Moving Average vs Exponential Smoothing: changing the conditional probability of C given A and B fail.*

The Bayesian network with initial conditional probabilities as shown in Figure 5.1, will be used to compare the effectiveness of the exponential smoothing method. Both the two-month moving average approach and the exponential smoothing model with a smoothing constant of 0.2 was applied to update the demand over a 24-month period.

With $\alpha = 0.2$ and $P(C|, A^c, B^c) = 0.01$, the expectation for C for the exponential smoothing method and the two-month moving average are 0.4894 and 0.645 respectively. The exponential smoothing appears to give the best one year ahead forecast based on the lower mean squared deviation of 0.05303 compared to 0.05717 for the two-month moving average (Table A.1).

Example 6. *Let us assume that the conditional table for C is updated for* $P(C|A, B^c) = 0.9$ *and* $P(C^c|A^c, B) = 0.2$ *(Table 5.2) using prior data over a 24 month period (Table*

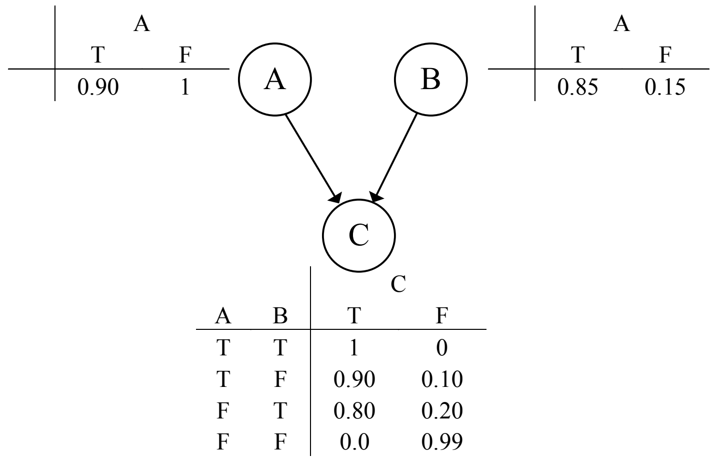


Figure 5.1: Initial Bayesian Network with conditional probability table

		C	
A	B	T	F
T	T	1	0
T	F	0.90	0.10
F	T	0.80	0.20
F	F	0.49	0.51
E(C)		0.65	0.35

Table 5.1: Conditional probability table of C after updating with the exponential smoothing approach

A.2).

After updating with the exponential smoothing method, $P(C|A, B^c)$ is reduced to 0.249 (Table 5.3) and $P(C^c|A^c, B)$ is increased to 0.559 (Table 5.4).

The change in $P(C|A, B^c)$ from 0.9 to 0.246 resulted in a decrease in the expectation of C from 0.3874 (Table 5.2) to 0.3482 (Table 5.3), while the change in

A	B	C: T	C: F
T	T	1	0
T	F	0.90	0.10
F	T	0.80	0.20
F	F	0.01	0.99
E(C)		0.39	0.61

Table 5.2: Conditional probability table of C before update for Example 6

A	B	C: T	C: F
T	T	1	0
T	F	0.25	0.75
F	T	0.80	0.20
F	F	0.01	0.99
E(C)		0.35	0.65

Table 5.3: Conditional probability table of C after update of $P(C|A, B^c)$

A	B	C: T	C: F
T	T	1	0
T	F	0.90	0.10
F	T	0.44	0.56
F	F	0.01	0.99
E(C)		0.26	0.74

Table 5.4: Conditional probability table of C after update of $P(C = T|A^c, B)$

A	B	C: T	C: F
T	T	1	0
T	F	0.25	0.75
F	T	0.44	0.56
F	F	0.01	0.99
E (C)		0.22	0.78

Table 5.5: Conditional probability table of C after $P(C = T|A, B^c)$ and $P(C|A^c, B)$ are updated

$P(C^c|A^c, B)$ from 0.2 to 0.559 resulted in a decrease in $E(C)$ to 0.258 (Table 5.4). It is significant to note that both changes separately and together affected the expectation of C. In table 5.5, $E(C)$ was decreased to 0.22 when $P(C|A, B^c) = 0.246$ and $P(C^c|A^c, B) = 0.559$.

In updating the probability using the exponential smoothing we are able to see the impact of the fluctuations or changes in the conditional probability table as well as changes in the expectation of C. In a larger network, where C is a parent node, this update would propagate throughout the network. The exponential smoothing updating of the probability table seems to be efficient in updating the table. It is also a much simpler method to update the Bayesian network than the approaches discussed in the literature review.

5.6.2 Neural Network

Artificial neural consists of neurons or cells that communicate by sending signals to each other over a large number of weighted connections (Krose and der Smagt, 1996), which mimics the manner in which the biological nervous system such as the brain processes information. Artificial neural network has diverse applications such as financial predictions, machine vision, medicine and data mining. Network structures of the neural network are Perceptron (Rosenblatt, 1958), Artron (Lee, 1950), Adaline (Widrow and Hoff, 1960), Madaline (Widrow and Winter, 1988), Back-propagation network (Rumelhart et al., 1986), Hopfield network (Hopfield, 1982) and Counter-Propation network (Hecht-Nielsen, 1987). There are other structures that may combine some of these fundamental structures or build on some to form other structures.

Neural networks facilitate solving complex and mathematically ill-defined problems using simple computational operations such as additions, multiplication and fundamental logic elements. According to Graupe (2006), artificial neural network will be computationally and algorithmically very simple and will have a self-organizing feature to allow it to hold for a wide range of problems. Another advantage of the neural network is that it is element-wise parallel, unlike a computer, a sequential machine, which will result in the entire system (computer) failing in the event one transistor fails. The neural network simulates a biological neural network, which allows for very low programming to solve complex problem that are non-linear and/or non-analytical and/or stationary and/or stochastic.

The neural network is also able to deal with incomplete information or noisy data and can be very effective especially in situations where it is not possible to define the rules or steps that lead to the solution of a problem. The data could have missing values where some variables are unobserved or hidden variables where the variables are never observed or might not even exist. In these instances there are different algorithms such as the neural network can be applied to derive the structure of the network in the supply chain. In fact, neural network can be used to model data with hidden variables. The neural network is the multilayer perceptron network, which is also known as back-propagation, or feedforward network. The neural network takes in a set of real inputs and computes one or more output values and possible using some number of layers of hidden units. That is, the learning algorithms, given the inputs, adjust the weights to produce the required output. So the network can learn how to recognize input patterns.

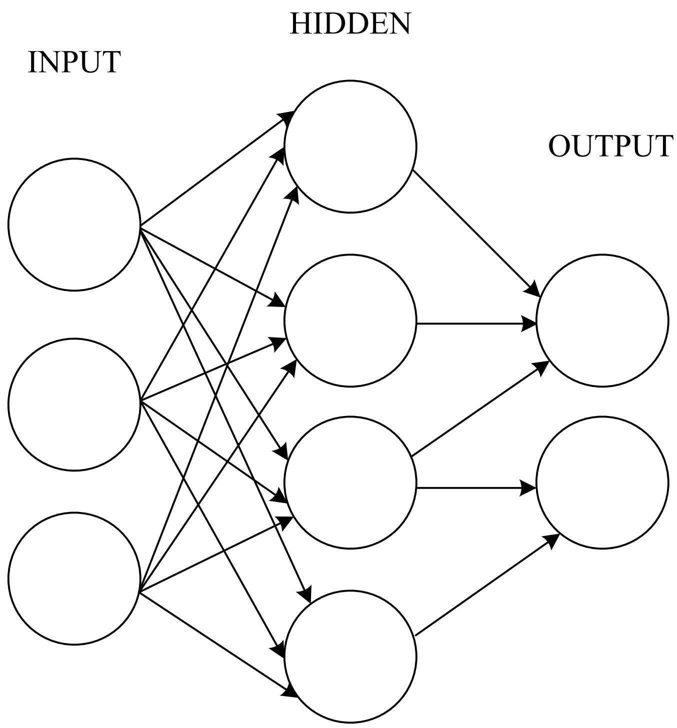


Figure 5.2: Neural Network structure that could have several hidden layers

Neural networks are a powerful technique to solve many real world problems.

They have the ability to learn from experience in order to improve their performance and to adapt themselves to changes in the environment. The network can be trained by first choosing random initial weights after which the training or learning will follow. The learning method can be supervised, unsupervised or reinforced. In supervised training, both the inputs and the outputs are provided. In unsupervised training, the network is provided with inputs but not with desired outputs. The system itself must then decide what features it will use to group the input data or the network has to make sense of the inputs without outside help. This is often referred to as self-organization or adaption.

The neural network works well for modeling deterministic models (Fernandez-Rodrzguez et al., 2000). The back-propagation algorithm for the neural network (Rumelhart et al., 1986) minimizes the sum of squares of the differences between the output and the actual value of the training data. However, this algorithm may be limited in identifying the fluctuation in the data. Therefore, stochastic neural network (Kamitsuji and Shibata, 2004) would be more suitable for learning changes in the network. Stochastic neural network is a hierarchical network of stochastic neurons that emit 0 or 1 with the probability determined by the values of inputs. A stochastic neural network introduces random variations into the network.

The neuron is the basic processor in neural networks. In the neural network all the neurons (Figure 5.2) are interconnected. There is one output per neuron, which is related to the state of the neuron or its activation, which may fan out to several other neurons. Each neuron receives several inputs I_j over these connections, called synapse. The neurons continuously evaluate their output by looking at their inputs, calculating the weighted sum and comparing to a threshold to decide if they should fire. The inputs are the activations of the incoming neurons multiplied by the weights

w_j of the synapses. All the knowledge that is acquired in a neural network is stored in the synapses, the weights of the connections between the neurons. Once there is some form of knowledge in the weights of the network, presenting a pattern for input to the network will produce the correct output. There is a weight adjustment that needs to follow the learning law. The activation of the neuron is computed by applying a threshold function to this product.

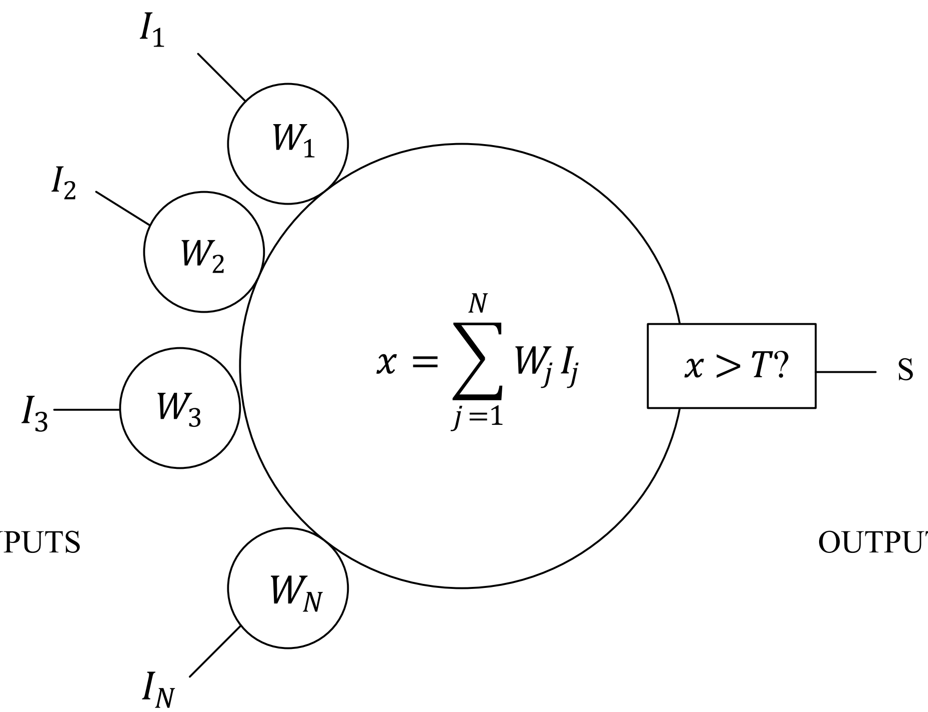


Figure 5.3: Basics of an Artificial Neuron Network

The activation function behaves like a squashing function, such that the output of the neurons in a neural network is between certain values. There are three types of activation functions-threshold function, piece-wise linear function and sigmoid function. The threshold activation function, $f(\cdot)$, is usually a nonlinear, bounded and piecewise differentiable function such that

$$f(x) = \begin{cases} 1 & \text{for } x > 0 \\ 0 & \text{for } x = 0 \\ -1 & \text{for } x < 0 \end{cases} \tag{5.2}$$

where

$$x = \sum_{j=0}^{N} w_j I_j \tag{5.3}$$

Another popular class of function is the sigmoid or squashing functions. An example is the logistic function:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5.4}$$

The logistic function is a simple non-linear function and the derivative can be easily calculated, which can be important when calculating the weight updates in the network. It thus makes the network easier to manipulate mathematically. This has been an attractive feature for early computer scientists who needed to minimize the computational load of their simulations. It is commonly seen in multilayer perceptrons using a back-propagation algorithm. In order to use activation function in a multilayer network the activation function must be nonlinear; otherwise the computational power will be equivalent to a single-layer network.

If $f(x)$ is stochastic, the output is determined probabilistically by a distribution selected according to x, such that

$$f(x) = \begin{cases} 1 & \text{with probability } \frac{1}{1+e^{-x}} \\ 0 & \text{otherwise} \end{cases} \tag{5.5}$$

Other sigmoid functions are available; another popular alternative is the hyperbolic tangent function: $f(x) = \tanh(x)$.

5.6.2.1 Supervised Learning using the Neural Network Approach

Example 7. *In this example we examine a supervised neural network training for an OR gate, where boolean inputs (true or false) are used and a single Boolean output is returned with learning rate (LR) 0.2. The weights are updated at each iteration from the previous calculations (Table 5.6).*

In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then calculated, causing the system to adjust the weights, which control the network. This process occurs over and over as the weights are continually fine-tuned (Table 5.6).

5.6.3 Analysis of the Neural Network and Exponential Smoothing Approach

With the aid of an example, we will compare the effectiveness of the exponential smoothing and neural networks as methods for updating the probability table of the Bayesian Network in the supply chain.

Threshold	Input			Initial Weight		Calculated Output		Sum	Network	Error	Correction	Final Weight	
TH	I_1	I_2	*Z*	w_1	w_2	C_1	C_2	*X*	*N*	*E*	*R*	W_1	W_2
								$C_1 + C_2$	*If (X >TH,1,0)*	*Z - N*	*LR*E*	$R + w_1$	$R + w_2$
0.5	0	0	0	0.2	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.4
0.5	0	1	1	0.2	0.4	0.0	0.4	0.4	0.0	1.0	0.2	0.4	0.6
0.5	1	0	1	0.4	0.6	0.4	0.0	0.4	0.0	1.0	0.2	0.6	0.8
0.5	1	1	1	0.6	0.8	0.6	0.8	1.4	1.0	0.0	0.0	0.6	0.8
0.5	0	0	0	0.6	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.8
0.5	0	1	1	0.6	0.8	0.0	0.8	0.8	1.0	0.0	0.0	0.6	0.8
0.5	1	0	1	0.6	0.8	0.6	0.0	0.6	1.0	0.0	0.0	0.6	0.8
0.5	1	1	1	0.6	0.8	0.6	0.8	1.4	1.0	0.0	0.0	0.6	0.8
0.5	0	0	0	0.6	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.8
0.5	0	1	1	0.6	0.8	0.0	0.8	0.8	1.0	0.0	0.0	0.6	0.8
0.5	1	0	1	0.6	0.8	0.6	0.0	0.6	1.0	0.0	0.0	0.6	0.8
0.5	1	1	1	0.6	0.8	0.6	0.8	1.4	1.0	0.0	0.0	0.6	0.8

Table 5.6: Supervised Neural Network Training – Updating Weights

5.6.3.1 Comparison of the Neural Network and the Exponential Smoothing Approach

Example 8. *A comparison of the exponential smoothing and neural network as updating techniques are examined by changing the learning rate (LR) and the smoothing constant (α). In this particular example the inputs are I_1, I_2 and I_3 with weights w_1, w_2 and w_3 respectively (Figure 5.4). In order to compare exponential smoothing and the neural network methods as probabilistic updating method we ran various scenarios, with the value of I_1 and I_2 being all ones, various values for I_3 that will be discussed later on, and the weights w_1, w_2 and w_3 initial value set to 0.1, 0.4 and 0.3 respectively. The probability is then updated over 50 data points and analyzed for each scenario, with different values of alpha (α) and learning rate (LR).*

First we will examine how the neural network approach behaves when we change the learning rate (LR) and how the exponential smoothing reacts to a change in α. When learning rate is 0.1 the neural network is very constant around 0.8 with sharp

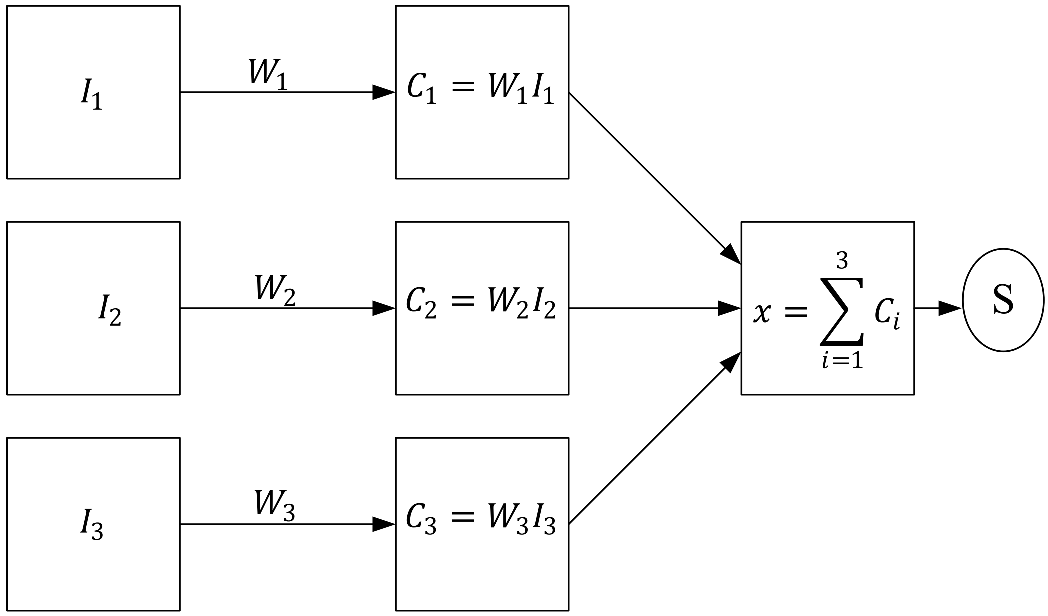


Figure 5.4: Neural Network of Example

spikes when $I_3 = 0$ (Figure 5.6). As the learning rates (LR) increases, the probability becomes more erratic (Figure 5.6). Looking at the exponential smoothing case (Figure 5.5), the sharp spikes in the data have a greater variation than the neural network when $I_3 = 0$ (Figure 5.6).

In general, the neural network seems to be smoother than the exponential smoothing (see Figure B.1-B.3). The variability of the exponential smoothing is also more than the neural network. As the learning rate and alpha increases by increment of 0.1 we see more variability in the probability for the exponential smoothing, while the probability remains close to 0.8 when using the neural network approach except for certain sharp drops in probability at certain points.

We can also examine how quickly the exponential smoothing and neural network model adapt to change. We will examine the probability update when there is a step

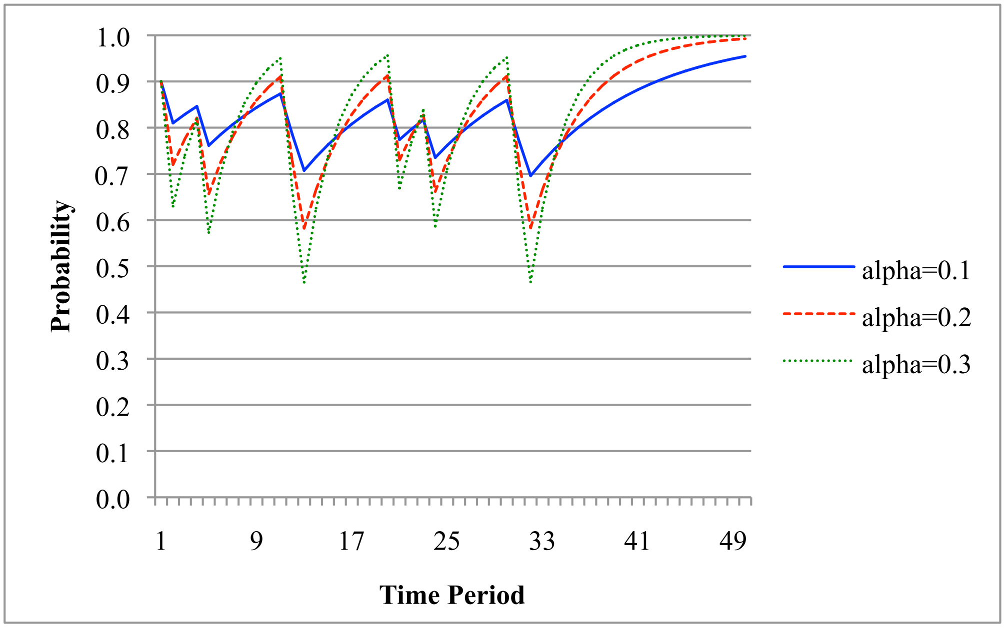


Figure 5.5: Exponential Smoothing results with various alphas

change, that is when the input I_3 changes from being 1 to 0 as well as when there is an impulse change from 1 to 0 at a particular point.

5.6.3.2 Step Change

Example 9. *In the step change scenario, we examined how the models adapt to the change when the input* I_3 *has the value of 1 for the first eighty percent of the data and then changes to 0 for the last twenty percent of the data points.*

The probability is close to 1 for exponential smoothing and close to 0.8 for neural network. From the figures below (Figure B.4-B.6), for α=0.1, 0.2, 0.3 and $LR = 0.1, 0.2, 0.3$ the probability drops for both the neural network and the exponential smoothing. However, the probability approaches zero faster in the exponential smoothing as α increases from 0.1 to 0.3 (Figure 5.8), in comparison to the neural

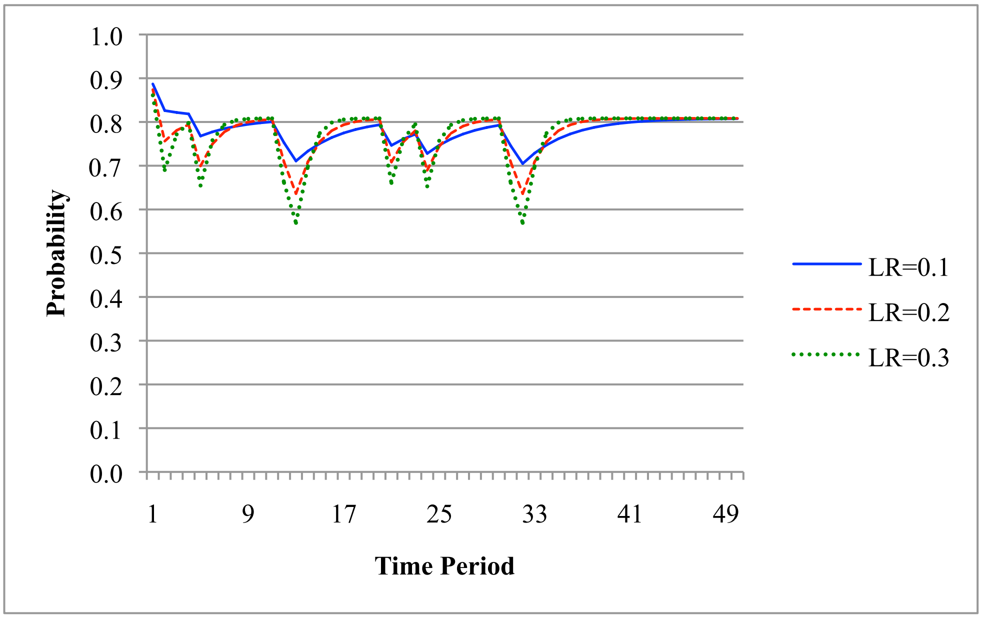


Figure 5.6: Neural Network results with various learning rates (LR)

network as the learning rate (LR) approaches 0.3 (Figure 5.7).

5.6.3.3 Impulse Change

Example 10. *In the impulse change scenario, input I_3 has all values of one and a zero value at point 25 in the data.*

For $\alpha = 0.1, 0.2, 0.3$ and $LR = 0.1, 0.2, 0.3$, when I_3 is 0, there was a drop in probability in both the neural network and the exponential smoothing approach (Figure B.7-B.9). However, there was a larger decline for the exponential smoothing approach with a slower recovery time. Applying different values of alpha and LR, the neural network tends to recover faster than the exponential smoothing. As a result of the impulse change in I_3, it would appear that the neural network recovers quicker than the exponential smoothing as the learning rate (LR) increases (Figure 5.9). Similarly, as alpha increases the exponential smoothing recovers faster from the

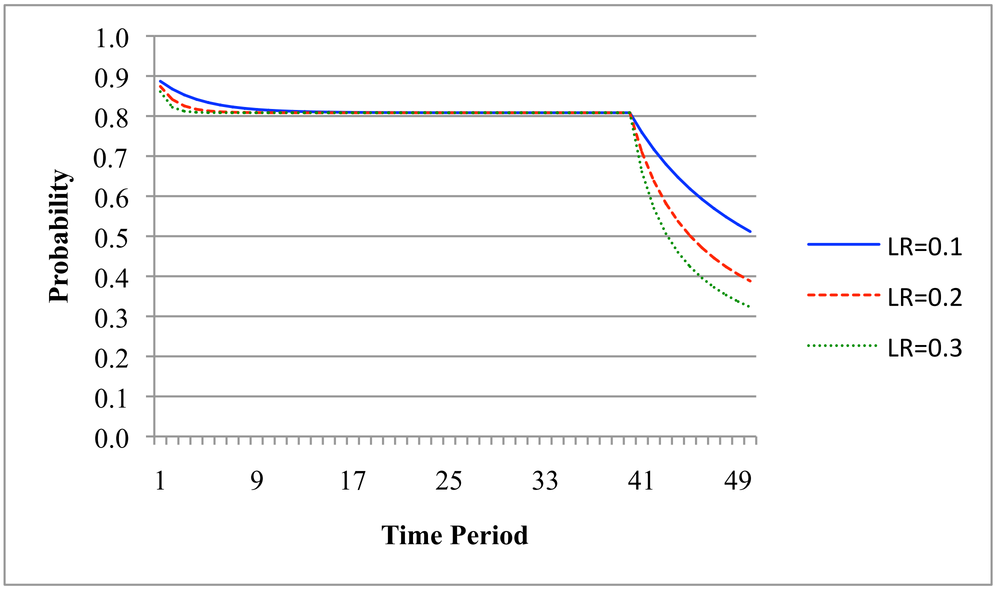


Figure 5.7: Step change: Neural network update with LR=0.1, 0.2 and 0.3

change in I_3 (Figure 5.10).

5.7 Conclusions

This chapter examined two ways in which the probability table of the nodes in the supply chain can be updated. In order to make decisions, it is useful to have up to date information about the system. These are the exponential smoothing and neural network. An example is used to compare the exponential smoothing and the neural network, which examined how a change in the probability propagates through the network and how the system is affected. The result of this comparison indicates that the neural network would be a better updating approach that the exponential smoothing. We would like to examine further how we could use the neural network to update probabilities in the Bayesian network.

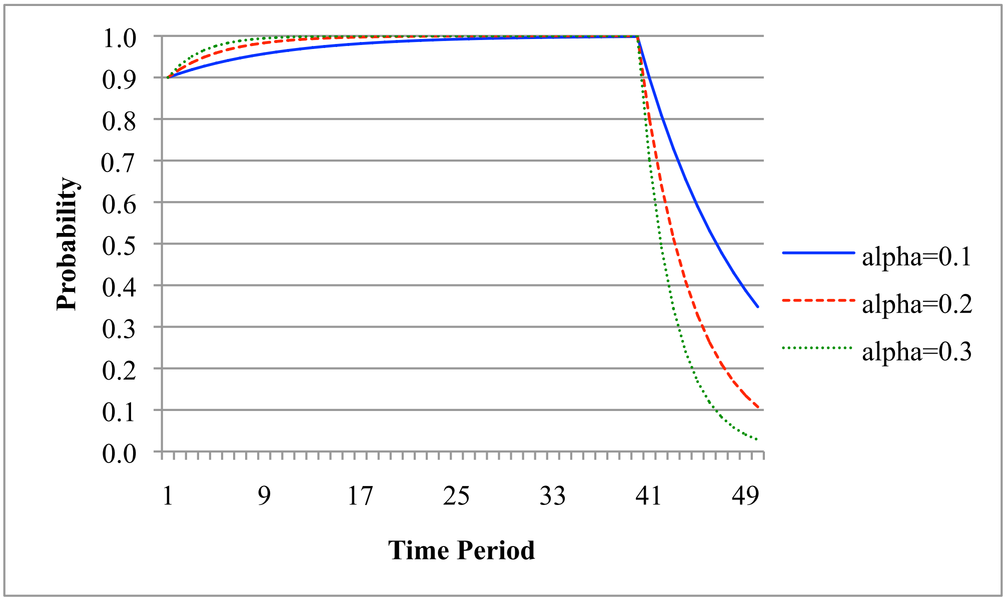


Figure 5.8: Step Change: Probability update using Exponential Smoothing with α=0.1, 0.2 and 0.3

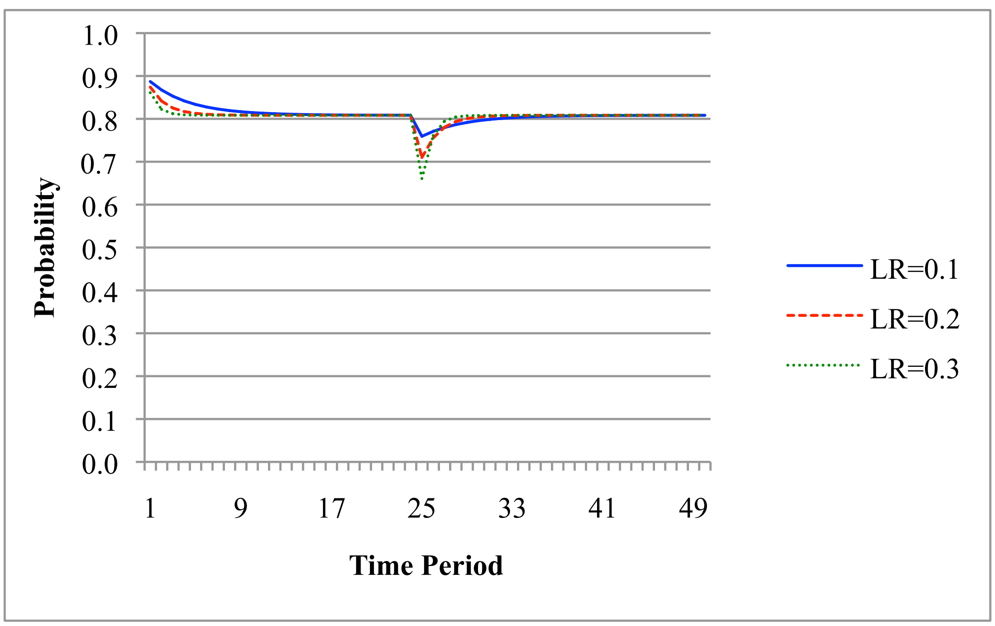


Figure 5.9: Impulse change: Neural network update with LR=0.1, 0.2 and 0.3

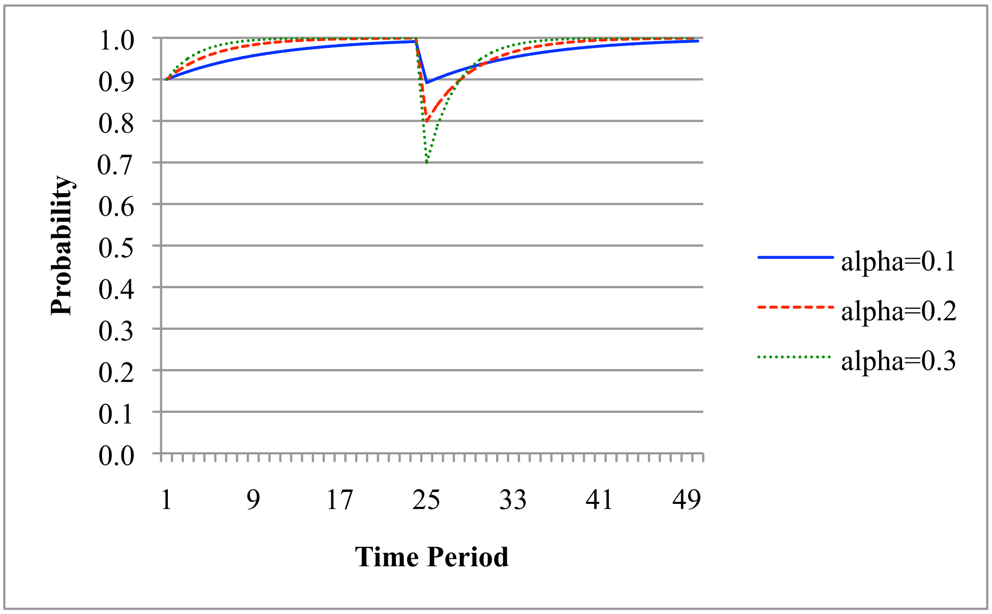


Figure 5.10: Impulse change: Probability update using Exponential Smoothing with α=0.1, 0.2 and 0.3

CHAPTER 6
CONCLUSIONS AND FUTURE WORK

6.1 Introduction

Supply chains are subject to external risks caused by unforeseen events that could range from natural to man-made event. The event may impact one or more levels of the supply chain and result in catastrophic disruption in the supply chain. However, before a company can mitigate the risks associated natural or man-made disasters, a greater understanding of the supply chain vulnerabilities is essential. In this paper an extended Bayesian network is proposed to represent the cause-and-effect relationships in an industrial supply chain. With the aid of the impact factors developed and the updating of the probability tables to predict future events we have the ability to diagnose the most vulnerable area in the supply chain and implement changes in order to increase the reliability of the system.

6.2 Research Contributions

The contributions of this work can be summarized as follows:

1. *A network based methodology for modeling decision making in a supply chain system is proposed.* This methodology Bayesian Network which has several potential attractive features: It has the ability to handle the complexity of the supply chain. The graphical nature of the Bayesian Network allows for easy visualization of the network. Therefore, the graphical representation makes it easy for users to visualize the problem as well as identify the vulnerable areas.

2. *A methodology is proposed to model disruption in the supply chain. Two impact factors are developed in this research to identify vulnerable nodes to a failure in*

the system. Modeling disruptions allows us the ability to analyze the supply chain as a system, understand the vulnerable areas in the supply chain, and make implementations to improve the robustness and reliability of the system. Utilizing the Impact factors, the user is able to identify areas that are susceptible or vulnerable to a disruption. Therefore, changes would be implemented in the more vulnerable areas.

3. *The methodology developed is applied to an industry example.* The research looks at a small supply chain. This work can be applied to real world supply chain problems.

4. *Bayesian Network learning methodology exponential smoothing and neural networks, are examined to update the probabilities in a supply chain disruption model.* Modeling the complexity of the supply and updating allows for further insight into the behavior of the supply chain in the event of a disruption.

In order to reduce the impact of a supply chain disruption, it is best to be prepared for the worst-case scenario. The methodologies presented in this dissertation provided a tool for supply chain managers to conduct a failure assessment in order to analyze the supply chain network. Special attention will be given to nodes in the network that are vulnerable to a disaster. By examining the vulnerability of the supply chain network, supply chain managers will be able to mitigate risk and develop quick response strategies in order to reduce supply chain disruption. Therefore, necessary changes will be implemented to increase the reliability of the system. However, modeling these complex supply chain systems is a challenging research.

6.3 Future Work

1. *Application of the methodologies developed in this thesis to other complex systems.* The methodologies developed have been applied to the supply chain. However, these models can be applied to any network where a disruption could have a profound impact on the network. For example, information systems, energy grids (eg. blackout on east coast), logistics, transportation (eg. airlines), ground (eg. UPS, FEDEX, freight), military (response to terrorism), natural disasters (eg. Katrina and Haiti).

2. *Use the methodologies developed in this thesis to make decision in real time. Explore the updating of the probability table with minimal time delay.* Timing is very important in reducing the impact of a failure or disruption in the supply chain. The data should be updated quickly enough so that changes can be implemented in a timely fashion to mitigate the impact of a failure or glitch in the system.

3. *Explore learning. Examine the smaller parts of the system (granularity) for learning in the extended Bayesian model.* In this dissertation, the neural network is more efficient than the exponential smoothing updating method in updating the probability distribution. However, a more thorough investigation of learning in the Bayesian Network can be explored further. Utilizing Bayesian learning to predict where failures may occur and address such issues accordingly.

4. *Due to the dynamic nature of the supply chain, the Bayesian Network can be developed further to be adaptive.* Extend the methodologies develop to account for the dynamic nature of the supply chain.

5. *Develop an interface that takes into account human factors.* The complexity

of the supply chain at times can be overwhelming to analyze and implement changes as the network grows. A computer-based program that generates alerts would assist in the effectiveness and efficiency of the response to a disruption.

APPENDIX A
THE UPDATE OF THE CONDITIONAL PROBABILITY TABLES OVER A 24 MONTH PERIOD

t	A_t	Two month moving average	Exponential Smoothing
1	0.010		0.010
2	0.015	0.013	0.011
3	0.011	0.013	0.011
4	0.020	0.016	0.013
5	0.025	0.023	0.015
6	0.036	0.031	0.019
7	0.250	0.143	0.066
8	0.300	0.275	0.112
9	0.400	0.350	0.170
10	0.400	0.400	0.216
11	0.300	0.350	0.233
12	0.300	0.300	0.246
13	0.010	0.155	0.199
14	0.300	0.155	0.219
15	0.500	0.400	0.275
16	0.600	0.550	0.340
17	0.020	0.310	0.276
18	0.030	0.025	0.227
19	0.260	0.145	0.234
20	0.450	0.355	0.277
21	0.500	0.475	0.321
22	0.800	0.650	0.417
23	0.890	0.845	0.512
24	0.400	0.645	0.489
MSD		**0.057**	**0.053**

Table A.1: Updating of the the probability table using the Moving Average and the Exponential Smoothing approaches (see example 5)

t	A_t	
	P(C | A, B^c)	P(C^c | A^c, B)
1	0.90	0.20
2	0.85	0.18
3	0.90	0.20
4	0.56	0.17
5	0.62	0.23
6	0.30	0.60
7	0.25	0.80
8	0.36	0.90
9	0.18	0.20
10	0.26	0.21
11	0.50	0.23
12	0.26	0.50
13	0.24	0.15
14	0.21	0.20
15	0.65	0.10
16	0.25	0.30
17	0.26	0.25
18	0.21	0.80
19	0.36	0.70
20	0.23	0.65
21	0.03	0.80
22	0.23	0.23
23	0.25	0.75
24	0.23	0.65
Exponential Smoothing	**0.246**	**0.559**

Table A.2: Updating the conditional probability table using the Exponential Smoothing approach (see example 6)

APPENDIX B
GRAPHS COMPARING THE EXPONENTIAL SMOOTHING AND THE NEURAL NETWORK APPROACHES

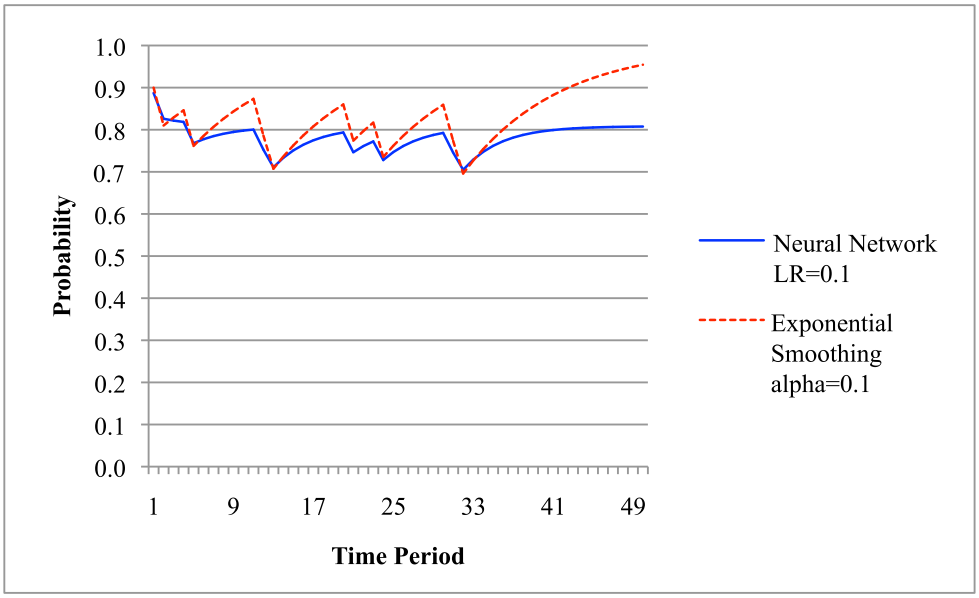


Figure B.1: Comparison of Neural Network and Exponential Smoothing on Data, α=0.1 and LR=0.1

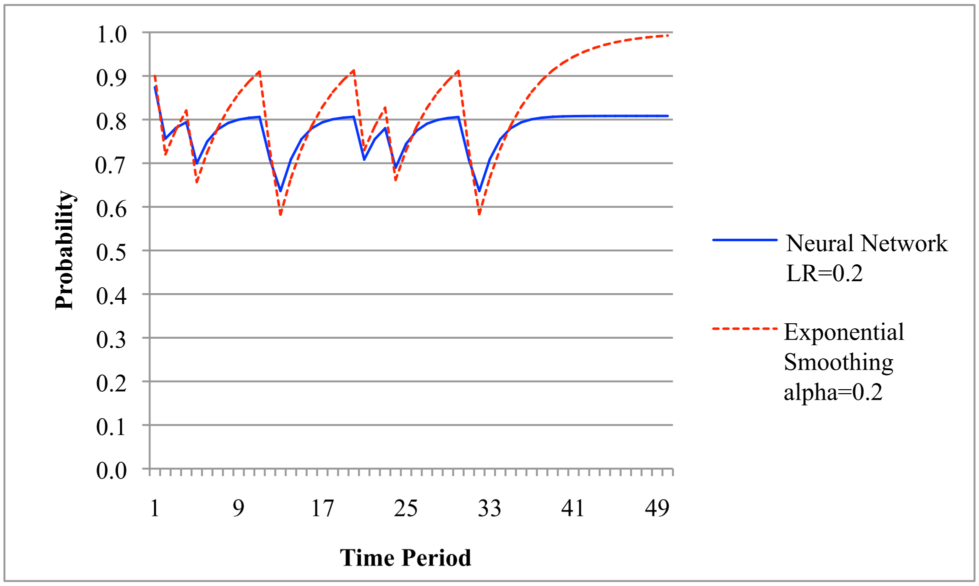


Figure B.2: Comparison of Neural Network and Exponential Smoothing on Data, α=0.2 and LR=0.2

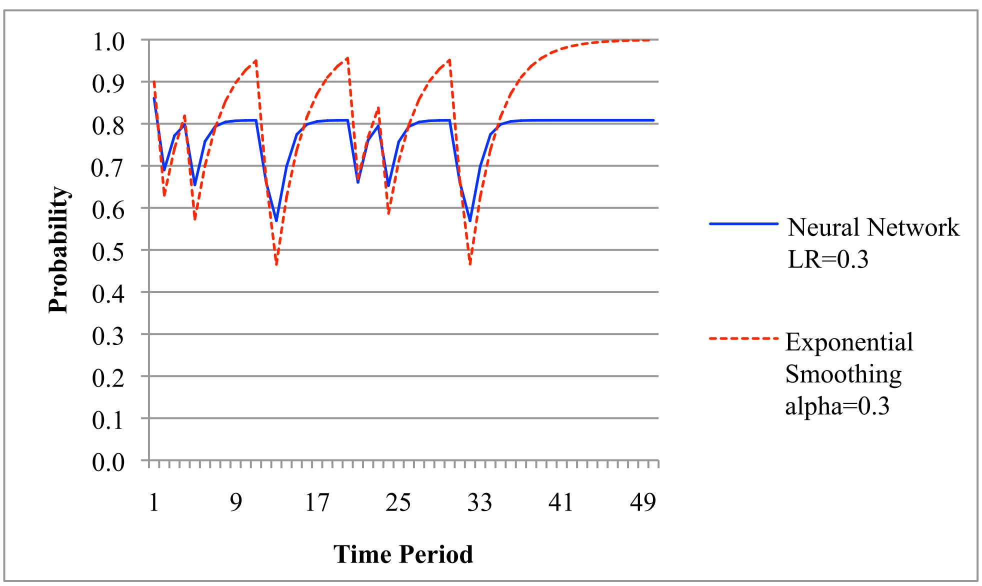


Figure B.3: Comparison of Neural Network and Exponential Smoothing on Data, α=0.3 and LR=0.3

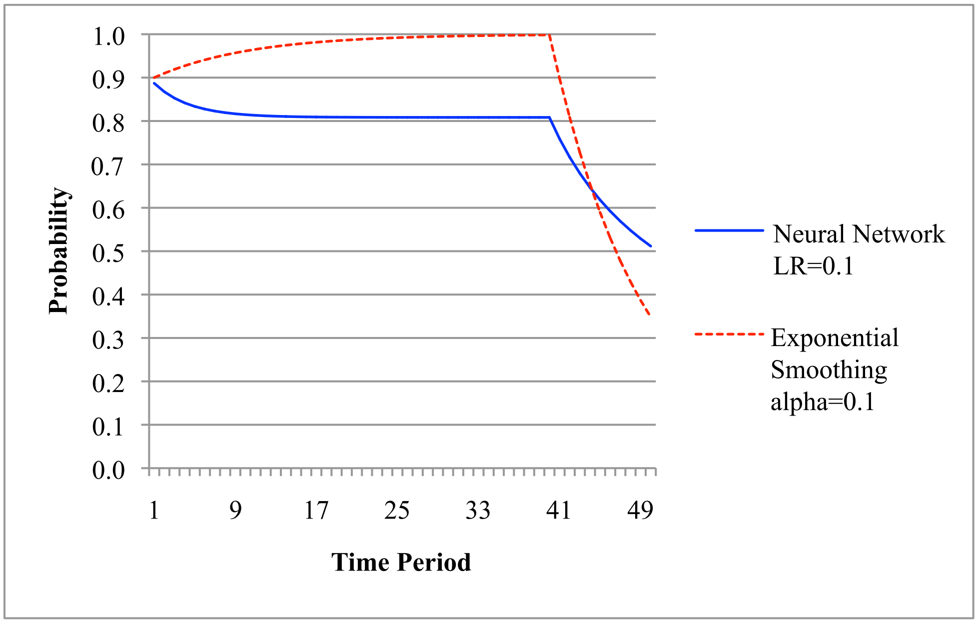


Figure B.4: Step change: Neural network versus Exponential Network on data, α=0.1 and LR=0.1

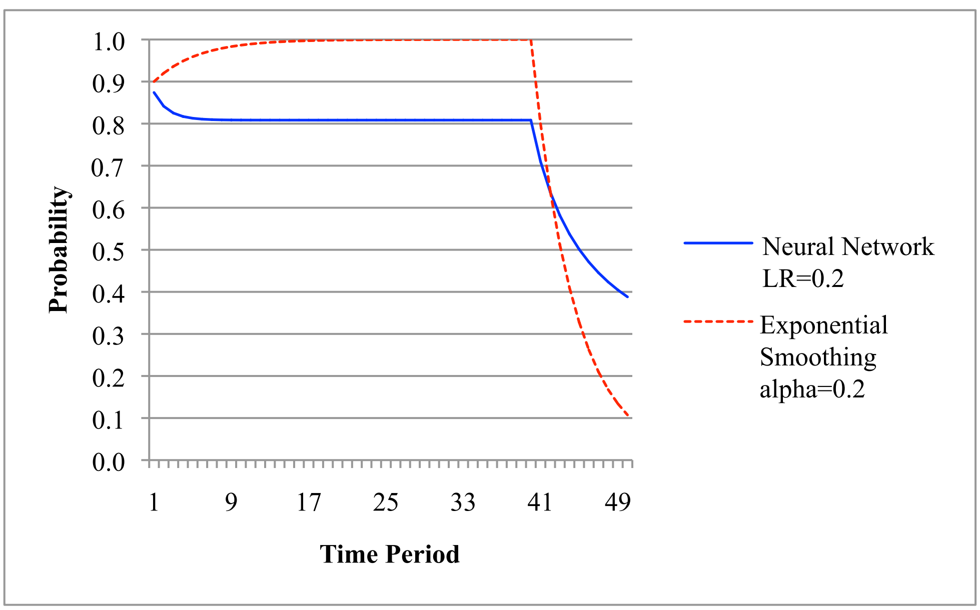


Figure B.5: Step change: Neural network versus Exponential Network on data, α=0.2 and LR=0.2

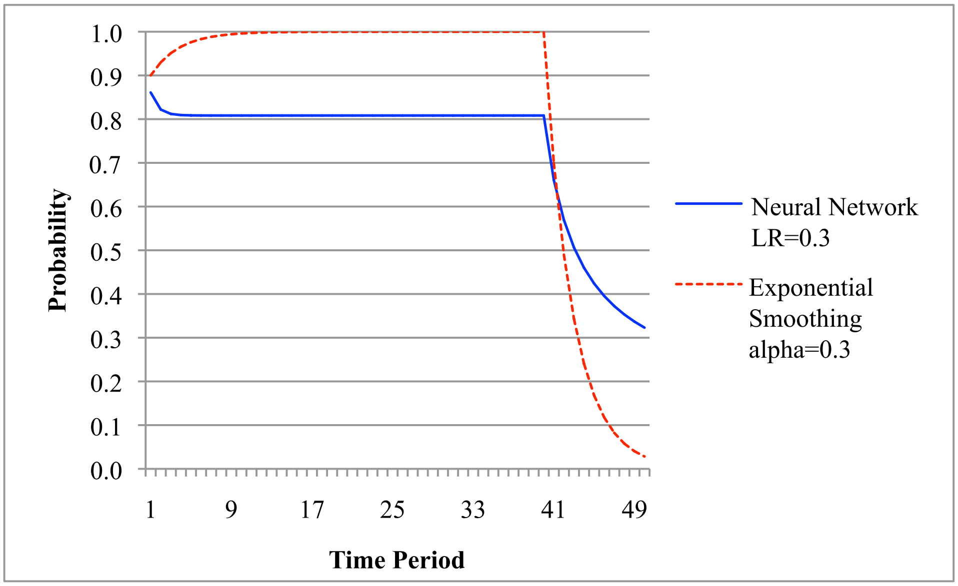


Figure B.6: Step change: Neural network versus Exponential Network on data, α=0.3 and $LR = 0.3$

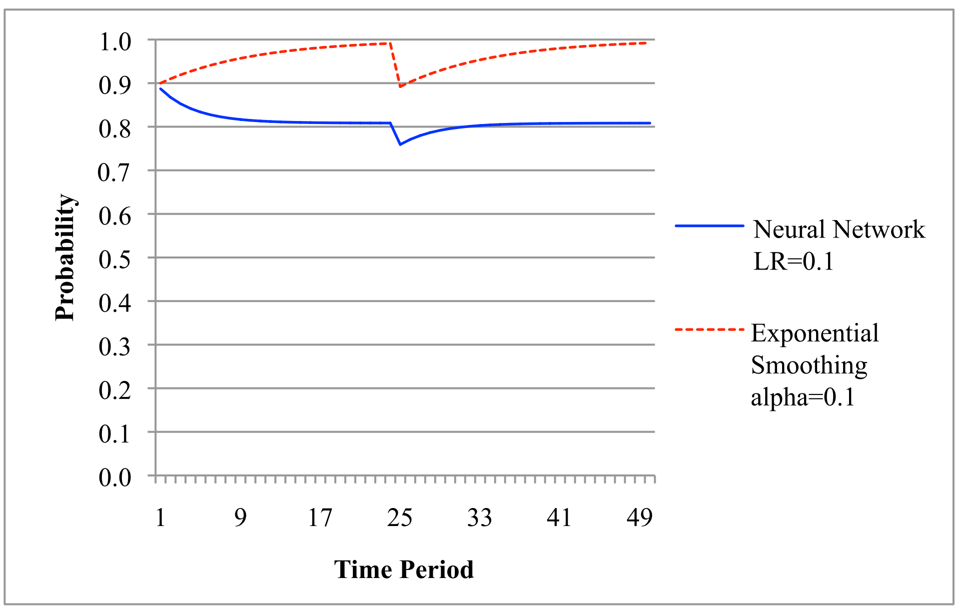


Figure B.7: Impulse change: Neural network versus Exponential Network on data, α=0.1 and LR=0.1

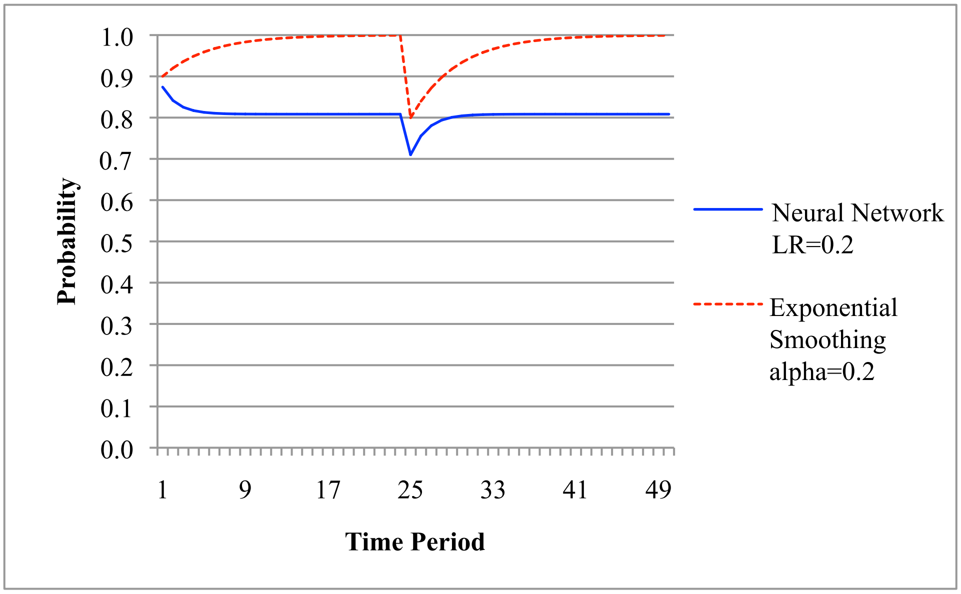


Figure B.8: Impulse change: Neural network versus Exponential Network on data, α=0.2 and LR = 0.2

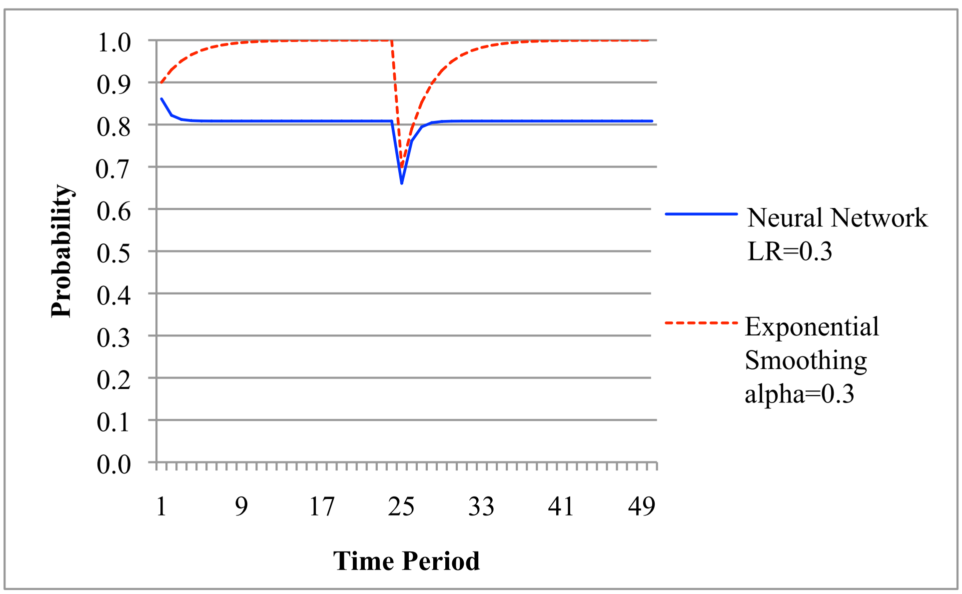


Figure B.9: Impulse change: Neural network versus Exponential Network on data, α=0.3 and LR=0.3

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