Supply Chain Risk Assessment through Data-Driven Bayesian Networks

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The supply chain is an integrated process of suppliers, plants, warehouses, and manufacturers all working together in an effort to procure raw materials, process the raw materials into final products, and deliver the final products to customers. However, the supply chain today has grown into a complex network, leading to vulnerabilities and an increase of uncertainty for decision makers. These vulnerabilities are defined as events with an associated likelihood to cause disruptions. With a limited amount of information on events occurring, the uncertainty decision makers encounter ultimately impedes the goals of the supply chain. These consequences are prevalent in low-volume, high-value supply chains such as the nuclear power generating industry.

The goal of this research is to reduce the uncertainty decision makers face in the nuclear power generating supply chain by developing a Bayesian network to monitor, plan, and control supply chain disruptions. The aim is to integrate models of event disruptions, resource availability, and mitigation options. Events that disrupt the flow of goods and information are identified through an ontological approach and are quantified with a likelihood of occurring through a general elicitation method. Resource availability of the nuclear power generating supply chain is modeled using control theory to simulate inventory data. The inventory data of upstream suppliers is estimated using Kalman filters and particle filters. The likelihood of events and the resource availability data are integrated into a Bayesian network depicting the nuclear power plant supply network. Mitigation options are added to the Bayesian network to reduce the likelihood of events at a financial cost to deploy the option. Several scenarios are used to illustrate the application of the Bayesian network in terms of the supplier selection problem to demonstrate how uncertainty in decision making is reduced.

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1.0 Introduction

1.1 Goals and Outcomes

The goal of this research is to develop a method to reduce the uncertainty in the nuclear power generating supply chain by exploiting new research and technology that exposes risks events to ultimately aid decision making when attempting to maintain the goals of the supply chain.

The supply chain today consists of individual, interdependent agents that procure raw materials, transform them into goods and deliver the products to the end customers. Within the past two years, the world has faced a vast amount of supply chain issues regarding events that impact the flow of resources and the material availability in several market sectors [2]. The supply chain continues to navigate the black swan event of the COVID-19 pandemic, whose ripple effects were first observed in the lumber industry and the hygiene paper market [58, 59]. In addition to black swan events, there exists a long list of events that can impact the supply chain resulting in undesirable effects. Transportation delays occurred when the container ship, Ever Given, was lodged in the world's crucial shipping artery, the Suez Canal. It was estimated that the stalled ship caused a loss of $10 billion a day by preventing other goods to move through the canal to their final destinations [68]. In the end, these events have the potential to produce severe economic consequences, imposing high risks to all industries. This includes the nuclear power industry, which is characterized by long lead-times and demand from a limited amount of suppliers due to highly customized products.

The ability to monitor, plan, and control the disrupting events and making well-informed decisions to support the supply chain goals is difficult. The uncertainty surrounding events has increased with the growing complexity of the supply chain. In terms of the nuclear power industry, there is more uncertainty due to the demand for unique qualifications of products and long lead-times. This consequentially clouds the decisions making process, leading to negative effects on the supply chain goals. By identifying and quantifying the uncertainties surrounding events as a likelihood of occurrence, supply chain professionals can monitor and manage the events, their uncertainties, and how they impact the major areas in the supply chain. With the ability to reduce the uncertainties, supply chain professionals can make decisions to successfully mitigate events, improve the flow of materials and reduce the consequences that may impede the supply chain goals.

Individual goals are identified and used to form a comprehensive approach to establish a method that will aid the decision making made by supply chain professionals using a risk-based decision making network. The goals and their impact are:

1. **Design a supply chain network with inventory-production models to generate synthetic supply chain data.** The supply chain exists as a network consisting of suppliers, plants, warehouses, and manufacturers identified commonly as agents. This network is modeled to illustrate the interdependent relationship between agents. The dynamics of the supply chain and inventory-production processes are introduced to the model to generate synthetic data. With the data, resource availability from participating suppliers is estimated. By having this estimate, the uncertainty surrounding the decision making process regarding procurement is reduced by knowing if and/or when a supplier's inventory has the desired product.
2. **Integrated models of risk, resource availability, and mitigation options within a graphical model of the supply chain network.**

   The graphical supply chain network model is integrated with the following: (1) a model of risk events and their consequences on the flow of goods, (2) a model of available resources from upstream suppliers, and (3) a model containing mitigation options to reduce the effects of risk events.

   The risk event model is illustrated to contain the risk events and potential disruptions that may occur in the four main areas of the supply chain [35]: (1) production, (2) inventory, (3) location, and (4) transportation. The propagating effects of the risk events are modeled with respect to lead-time and how the delay in the final product impacts the supply chain goals. Identifying and evaluating risk events with an estimate of its uncertainty as a probability of occurring enables transparency through the supply chain network and provides the ability to deploy risk management strategies to reduce their impact. Ultimately, this effort enables the use of additional monitoring and planning techniques that the decision makers have at their disposal.

   Resource availability is modeled as an estimate of inventory of upstream suppliers, which is shown graphically at participating agents in the supply chain network. Mitigation options are graphically depicted in the model to enable supply chain professionals the ability reduce the likelihood of a risk event occurring in order to maintain the goals of the company. The graphical model, with its integrated models, provide a visual aid of the entire supply chain network for the supply chain professionals, which includes where potential disruptions can occur and how decisions to mitigate them can be enabled.

3. **Monitor, plan, and control events and resource availability.**

   The ability to monitor, plan, and control the events and resource availability is an arduous task. There are a number of influencing uncertainties that may determine when a resource has become available or if an event occurred that increased the lead-time of a desired product. Some of these influencing uncertainties that impact the business goals of the company include political policies related to the companies commodity, market fluctuations, instability, and economic viability, technical uncertainties of commodity development, and the influence of all actors and agents in the supply chain to operate in harmony.

   In order for supply chain professionals to be effective, events are categorized in an attempt to understand how the events propagate throughout the supply chain. After categorization, the uncertainty surrounding events are assigned a probability to the demonstrate the likelihood of the event occurring. Supply chain professionals aim to find opportunities to improve resource availability; to some effect, this is the ability to match the ebb and flow of supply and demand in the supply chain. Moreover, resource availability depends on influencing uncertainties, customer-supplier relationships, and the demand forecasting and dynamic allocation of resources as a consequence of the relationship. By modeling events and resource availability in a comprehensive model, decision makers will have the ability to monitor events as a probabilistic assessment that has a likelihood of occurrence and an overall impact to the supply chain.

   Planning in the supply chain comes in the form of contingency plans and mitigation strategies to ensure the goals set by supply chain management are met. Contingency plans and mitigation strategies serve as a controlling mechanism to reduce the likelihood of events that may impede the goals of the supply chain. These contingency plans and mitigation strategies can range from supplier visits to ensure quality risks are deterred or the use of a supplier portfolio to choose a supplier that is geographically located in an area outside that is prone to natural disasters. In the event that mitigation strategies are appropriately planned then supply chain management has the ability to control risks events and their negative impact. To this end, decision makers are granted the ability to plan and control events in order to reduce their negative impacts [30].

4. **Support decision making in the supplier selection process through data-driven models.**

   The supply chain has grown into a complex network with a number of interdependent agents. As the supply chain stretches across the globe, companies are more prone to risk events and uncertainties increase due to vast number of players in the supply chain system. This in turn clouds the decision making process when attempting to satisfy the goals set by the supply chain. One decision clouded by uncertainty is the supplier selection process. The process requires measuring the performance of each supplier and comparing their resilience to risk events in order to choose the supplier that satisfies the goals of the supply chain. By successfully completing the previous objectives, the uncertainty surrounding decision making is reduced by identifying how risk events impact the reliability of suppliers.

   This research helps aid supply chain professionals in deciding which supplier to choose in order to meet goals of the company. By including models of events, resource availability, and mitigation options for each supplier, then supply chain professionals have the ability to evaluate their supplier portfolio. Through this evaluation, supply chain professionals can analyze the risks surrounding each supplier and observe the likelihood that a supplier may encounter a disruption that impacts the lead-time. Supply chain professionals are able to finalize their decision on which supplier to choose from by selecting the supplier that encounters the least amount of disruptions.

1.2 State of the Art and Limits of Current Practice

Decision makers in supply chain management are up against a supply chain that is growing in size and complexity. Because of this, decision makers are more vulnerable to events that can disrupt the flow of resources, which clouds decisions in the supplier selection process or whether resources are available from suppliers. Research today treat each of these in isolation and fail to consider the causal relationship between events, the supplier selection process, and resource availability. There is a critical need to integrate all the uncertainties into one model to perform the following: (1) reduce the likelihood of disruption in the flow of goods and resources through mitigation techniques and contingency plans, (2) reduce the negative consequences of risk events on the supply chain goals by analyzing the supplier selection process, and (3) increase the likelihood that resources are available in the supply chain by appropriately modeling the push-pull nature of supply and demand.

This section highlights the state of the art dealing with the uncertainties encountered within the supply chain. It explains the approaches made by researchers that aid supply chain management in achieving their goals and the limitations of their approach. The remainder of this section highlights the state of the art concerning modelling the supply chain with its associated uncertainties and the limitations to their approach, followed by a brief overview of the current practices dealing with the supplier selection process along with their limitations. Finally, a discussion on how resource availability is currently studied along with the limits of their approach.

1.2.1 Supply Chain Modelling and Disrupting Events

Modelling a supply chain is an attempt to include all dependent agents (i.e. supplier, manufacturers, customers, etc.) in a supply chain that govern the flow of materials and information to its end-user [6]. This activity is typically defined as supply chain network design (SCND) and is considered the most basic decision made by supply chain management [93]. It includes designing the flow of raw material from suppliers, how they are turned into finished products, and finally delivered to end-customers in the most optimistic way [7]. A crucial component to modelling the supply chain network is including the potential disruptions and the uncertainties managing the risk events. Today, supply chains with their uncertainties are modeled by a wide range of methods. These methods cover applied uncertainty theory, fault-tree analysis, and elicitation techniques. The application of uncertainty analysis and theory method designed the supply chain model and the likelihood of occurrence of disruptions to counter supply chain issues [93]. Uncertainty theory is a mathematical system used for modeling decisions made in the state of indeterminacy [54]. Indeterminacy is a phenomena whose outcomes cannot be exactly predicted and is described quantitatively through belief degrees given by domain experts [53]. The approach to employ uncertainty theory to characterize the events encountered in the supply chain was chosen due to an inability to obtain valid data [93]. This required the use of domain expertise to develop a supply chain model and quantify risk events. However, the restriction to only using domain experts severely limits accuracy for model development. There exists legitimate data that can be used in parallel with domain experts to help develop the supply chain model [86]. Fusion between data and domain expertise to model the supply chain can be achieved through the use of Bayesian networks.

Bayesian networks are a type of probabilistic graphical model that can be used to build the supply chain model from data and/or expert opinion. Bayesian networks provide flexible frame-works to combine different data types and prior knowledge [95]. This ability to handle disparate and incomplete data provides a more accurate approach for modelling the supply chain and the uncertainties surrounding risk events.

Uncertainty theory does not provide the means to update degree of beliefs in the model. The inability to update the likelihood of occurrence hinders the accuracy of the model. The likelihood of events change over time and this dynamic behavior must be reflected in the model [75]. Updating the likelihood of occurrence can be accomplished through Bayes theory and thus strengthen the decision making capabilities of the model. As an example, ground transportation of resources may have more risk associated with it when road conditions are dangerous, much like those encountered in the winter time. In the event that a supplier is located in a region where snowfall occurs in the winter months, then the likelihood of a risk event delaying transportation increases during the winter months.

> *LIMITATION — Applications of uncertainty theory limit the supply chain modeling by using domain expertise, which restricts data usage and labels risk as static events. This fails to fully depict the dynamic nature of the supply chain and the evolution of impacting risk events with respect to time.*

Another approach to supply chain modelling was achieved by deconstructing a product being manufactured through its bill of materials [73]. The bill of materials provided a supply chain network for each component of the product, which was defined by the most basic services used in their manufacturing processes. Within these manufacturing processes, uncertainties were identified as potential sources of delay risks and were defined as the inability for the process to perform as intended thus delaying the delivery of the final product [72]. The delay risks were quantified as individual probabilities in terms of quality and capability deficiencies and were modeled using fault-tree analysis.

The formulation of a physical system into a structured logic diagram, which is used to analyze the causes that lead to the failure of a specified event of interest defined as the top event, is called fault-tree analysis [49]. The fault-tree graphically represents a logical relationship between the undesirable event and the basic events that may cause it. The logic developed provides a Boolean formula built over all combinations of basic events that will lead to the occurrence of the top event, creating a logical framework for understanding ways a system can fail [92].

The supply chain was modeled using the fault-tree analysis approach. The fault-tree related the delay risks in the manufacturing processes as basic events that can lead to the top event of failing to deliver the ordered product on-time. The top event was analyzed by structuring the basic events of the manufacturing services through two Boolean gates, AND gates and OR gates [73]. If a delay occurred at a manufacturing service, then the output of the given gate propagated through the fault-tree to show a failure to deliver on-time. This passage of fault-tree logic enabled supply chain management to proactively understand where in their supply chain network a risk may occur [72].

Although fault-tree analysis is effective in showing the consequences of delays, the method fails to model the complex environment of the supply chain by limiting the consequences of events to binary outcomes in Boolean logic. Additionally, the analysis of a single top event fails to reveal additional useful information in terms of risk management and decision analysis for supply chain professionals. Restricting the model to only binary events fails to identify the number of risks events that can cause delays outside the basic services in manufacturing processes. To account for these risks, the fault-tree model would become cumbersome with the addition of logic gates and the need to replace the logic to evaluate all scenarios. This requires the fault-tree to be reconstructed to consider all risks and undesirable events, which can result in a number of iterations of the fault-tree model when replacing the appropriate Boolean logic to evaluate the final top event. There is a critical need in supply chain modelling to account for all potential uncertainties in order to aid decision makers in the face of uncertainty.

Such an holistic approach to supply chain modelling can be achieved through Bayesian networks, which enables decision makers the ability to analyze risk events for more than single top events. Bayesian networks are ideal for analyzing complex sets of variables and representing the probabilistic relationships between them [16]. Through this approach, risk management and reasoning strategies can be deployed by recognizing all potential risk events and to proactively maintain the supply chain goals.

There also exists a serious limitation in using static probabilities for basic events when using fault-tree analysis, when the likelihood of these basic events, or risk events, in the supply chain are dynamic in nature [75]. The Bayesian approach to modeling the supply chain presents a way to update the probabilities of events based on the arrival of new, relevant pieces of evidence [78]. By successfully updating the supply chain model with new evidence, then the uncertainty surrounding the events is reduced for supply chain professionals.

LIMITATION — Fault-tree analysis fails to comprehensively model the supply chain by constraining events to single failure events and defining their likelihood as static probabilities.

1.2.2 Supplier Selection

Another decision impeded by uncertainty in the supply chain is the supplier selection process. The supplier selection process is a strategic approach to selecting a supplier that meets a desired criteria. The supplier selection process is considered one of the key issues supply chain managers handle in order to remain competitive due to the number of uncertainties in purchasing situations [40]. Depending on the market, these uncertainties include the consideration of the product life cycle and an attempt to satisfy various quantitative and/or qualitative criteria for each potential supplier where this criteria for each supplier may be in the form of financial risks, quality assurance, or supplier resiliency [61].

In one approach, the uncertainties in the supplier selection process were identified using different linguistic scales and a performance criteria was obtained according to individual accounts for potential suppliers [40]. The performance criteria of each supplier was evaluated as a multi-criteria decision making (MCDM) problem. MCDMs are integrated decision-making systems that provide decision makers the ability to make decisions in domains where selection is highly complex [4]. The application of the MCDM modeled the decision process for supplier selection and the uncertainties encountered when evaluating the performance criteria of each supplier was addressed using fuzzy set theory [39].

Fuzzy set theory takes advantage of fuzzy logic, which is a way to model logical reasoning where the truth of a statement is not binary but rather a degree of truth ranging between zero and one [97]. Through fuzzy set theory, the desired goals of the decision makers in the supplier performance criteria was evaluated with a quality function deployment (QFD). Quality function deployment (QFD) is "an overall concept that provides a means of translating customer requirements into the appropriate technical requirements for each stage of product development and production (i.e., marketing strategies, planning, product design and engineering, prototype evaluation, production process development, production, sales)" [12]. The QFD in presented by Karsak used supply chain information through the MCDM model in an attempt to identify which of the supplier's attributes had the greatest impact on the goals established by the decision makers [40].

The supplier selection process that was evaluated in the MCDM model failed to identify the conditional relationship between supplier characteristics and supplier assessment qualities, for example, the relationship between quality and reliability for each supplier. In the supplier selection process, desired goal of maintaining a lead-time is dependent on risk events surround quality, which describes the reliability of a supplier to produce a product that meets those standards. To this end, not all uncertainties are revealed in the decision making for the supplier selection process. There exists a critical need to show the causal relationship between uncertainties in the supplier selection process to ensure the supplier selected meets the goals of the decision maker.

LIMITATION — Managing the supplier selection process through a multi-criteria decision making problem does not reduce uncertainty by failing to consider the conditional events that impact the criteria for supplier selection.

The supplier selection process can benefit a company's goals in many ways if the uncertainties are successfully managed. Properly navigating through these uncertainties of the supplier selection process not only promotes greater efficiency and lower cost for an entire supply chain network but also enhances the stability and robustness of the supply chain [34]. During the production process, suppliers may experience a number of operational risks. In order to overcome the uncertainties in operational risks, the supplier selection process promotes a technique, as was performed by Fang, for reducing the financial consequences by modeling a supplier portfolio [22].

The supplier portfolio characterizes each supplier by the common uncertainties of operational risks of defect rate and late delivery. The defect rate and late delivery were quantified through historical data and by treating the supplier portfolio as a risk portfolio, the final model was evaluated using the Value-at-Risk (VaR) theoretical tool. This tool is often used in the financial market to manage market risk. The tool takes into account a given time horizon and a confidence level to determine the value at risk as a loss in market value over the defined time horizon [52]. The VaR approach determined the risk exposure and helped identify a competent supplier portfolio. The uncertainties are limited by the confidence interval and a defined time horizon in the VaR assessment tools. Risks associated with the supply chain are dynamic and the probabilities of their occurrence change daily. There is a critical need to model and mitigate the risks as their probability of occurrence changes over time. For example, the risk associated with a impeding weather during hurricane season is more likely to disrupt the supply chain during a particular duration throughout the year. As the months continue and the season ends, the probability of occurrence decreases and an accurate model of a supply chain should reflect this behavior.

The VaR method bundles suppliers in a portfolio to measure the benefit of a collection of suppliers rather than the individual suppliers. In this case, the VaR method fails to measure individual suppliers, which would benefit the decision making process when selecting individual suppliers to meet their goals.

To this end, the supplier selection process needs to evaluate individual suppliers in order to reduce purchasing risk and maximize overall value to the end customer [80].

> *LIMITATION — Risks and uncertainties within the supplier selection process are limited to a specified period with a degree of confidence rather than a shifting degree of belief that the risk will occur with time. Suppliers should be evaluated on an individual basis rather than in a collective portfolio in order to reduce purchasing risk.*

1.2.3 Resource Availability

Decision makers in the supply chain encounter a fundamental process to effectively match supply and demand to ensure the incoming orders matches the work-in-progress and that the output of resources reaches their customer in the allotted time [25]. The very nature of supply and demand is clouded by uncertainty, placing the decision makers at odds against a number of influencing drivers that determine when resources may become available [87].

In one approach, the most significant drivers that influence resource availability was studied in order to inform decision makers on how to maximize resources in a biomass resource market model. This biomass resource market model developed a baseline using a literature review for each influencing driver and forecast how the driver may change and impact supply. Through this analysis, the influencing drivers reflected the variances and dynamics that controlled the supply, which was collected in a database where a series of 'literature informed' averages for each driver was calculated. Thereafter, the averages were projected into the future to estimate the resource availability for years to come [87]. The averaged literature review proposed by this approach fails to successfully forecast the behavior of inventory-production strategies that are governed by push and pull type supply chains. Resources in the supply chain follow a push and pull behavior, which is identified as a supply chain performance strategy [94]. Within these strategies, the uncertainties surround available inventory follow the inventory-production dynamics and how different allocations of inventory impact overall risk [18]. A better alternative is to generate synthetic data by accurately modelling the inventory-production process of a supplier given a demand input. This approach to resource availability would account for the push-pull nature of supply and demand, which will enable decision makers to predict and plan when the available resources are acquirable to fit their company's goal.

LIMITATION — Resource availability was accounted for using a static averaged to project future supply. Available resources depend on the push and pull type supply chain strategies, which can make the inventory count of suppliers fluctuate.

1.3 Research Approach

In order to overcome the state of the art and limitations of current practices, this research approach involves a data-driven decision making model through the use of a Bayesian network. The Bayesian network is constructed to mimic a supply chain network. For supply chain network development, an ontology surrounding the supply chain is used for the basis of supply chain agent relationships and their dependencies, risk event definitions, and overall flow of goods and resources. In this case, an ontology defines the basic terms and relationships in a shared conceptualization of a domain. The basic terms and relationships help formulate the interconnections between supply chain agents and the potential risks that can occur.

In addition to the supply chain network, an inventory-based manufacturing model is created to generate synthetic data representing inventory position and to perform particle filter estimation of suppliers using state-space representation. Process and measurement noise is added to account for uncertain fluctuations in the inventory measurement. State estimation techniques are employed to infer estimates of supplier inventory data and processes, including addition upstream suppliers. The synthetic data trains the resource availability of the Bayesian network and presents the degree of belief for inventory position of suppliers. The final Bayesian network includes potential events, their impact on lead-time, and how financial goals of the company with the addition of mitigation options to reduce likelihood of risk event occurrence at some monetary cost.

1.3.1 Supply Chain Network Development through Supply Chain Ontology and Data Mining

The supply chain today consists of individual, interdependent agents that procure raw materials, transform them into goods and deliver the products to customers through a distribution system [47]. By identifying the agents and their relationship with one another, a supply chain network can be graphically organized into its respective tiers of supplier, manufacturer, and distribution agents. By doing so, the graphic can depict the transformation and flow of goods from agent to agent until the product reaches its final destination or customer. However, creating a graphical representation of a supply chain network can be a difficult task due to the complexity of identifying all agents and their relationships in a particular supply chain. Typically, these tasks are completed by collecting data from participating agents through questionnaires via an elicitation technique. This adds more complexity to creating the network due to the need of communicating with vast amounts of supply chain agents thus requiring additional time and effort to successfully create the network.

To reduce time and effort, the supply chain network is developed through an ontology methodology [28]. This methodology captures the various supply chain concepts and their relationships among each other by combining data and information from multiple sources. In other words, the ontology methodology is a data integration approach resulting from data mining sources regarding the supply chain stages, functions, and decisions [85]. Once the ontology surrounding the supply chain is sufficient enough to understand the relationships and functions, then the supply chain network is created. This supply chain network depicts how resources and information flow between agents, where risk events may occur and their impact on the supply chain, and how decisions regarding contingency plans develop with respect to the financial goals of the company's supply chain in question [79].

1.3.2 Dynamic Supply Chain Model Development and State Estimation

This research requires data on inventory and production processes in order to gain useful information regarding resource availability of upstream suppliers. However, supply chain data contains sensitive information, which leads to companies protecting their data and a lack of sharing information across the supply chain as a whole [31]. In order to estimate the likelihood that a supplier has inventory, synthetic data is generated by modeling the supply chain through state-space representation with process and measurement noise to account for random fluctuations in inventory position and uncertainty of upstream suppliers. Two models are created to represent the supply chain dynamics between suppliers and the behavior of inventory position. The models respond to an abrupt change in demand depending on the parameters of the models. As a result, the response produces a typical inventory position or an inventory position that is saturated or low-in-stock.

The first model is a linear, series supply chain with demand acting as the input and the output is the supply of the first supplier in the series [64]. The second model depicts the behavior of a production and inventory system with a demand input on a make-to-order (MTO) manufacturer in series with a make-to-stock (MTS) manufacturer [90]. The model includes a nonlinear saturation around the inventory capacity of MTS manufacturer. The output represents the back order rate of the MTO manufacturer. Both models contain states representing the inventory position and other useful information of upstream suppliers.

State estimation is used to estimate inventory position of upstream suppliers. For the linear model, a Kalman filter is developed to estimate the inventory position of the immediate upstream supplier and the following supplier in sequence. The nonlinear model, containing the MTS and MTO manufacturers, a particle filter is developed to estimate the inventory levels of the MTS manufacturer and the back order rate of the MTS manufacturer. The parameters are adjusted to produce synthetic data containing a time-series inventory position for one year showing stable and unstable responses.

1.3.3 Bayesian Network Model Development

Risk analysis and modelling generally use a combination of qualitative and quantitative methods, such as fuzzy logic, fault-tree analysis, etc.. But these methods have some limitations — they cannot reflect the interdependence between risks and cannot be disseminated and updated after receiving new information. A more dominant method to study the risk is through Bayesian networks because they are most effective models for uncertain knowledge representation and analysis, which is superior for risk assessment of complex systems [23].

The constructed Bayesian network is a representation of the supply chain network, enabling the decision maker the ability to plan, monitor, and control the knowledge and data collected in the supply chain. The Bayesian network provides the decision maker with the probabilities of when risks may occur, including their relationship to the surrounding environment, and how they will impact the financial goals of the company. Additionally, the benefit of Bayesian networks include updating the network with qualitative evidence. In the Bayesian supply chain network, this depicts mitigation strategies and contingency plans to reduce the likelihood of risk events. To this end, the decision maker can actively observe unique probabilities over the Bayesian network variables representing the supply chain network while simultaneously attempting to satisfy the financial goals of the company.

1.4 Impact to the Nuclear Power Generating Industry

For advanced nuclear reactors to be cost effective, nuclear reactor technology must take advantage of improvements in advanced instrumentation and big data analytics in order to operate plants more efficiently, streamline maintenance, and have minimal staffing levels. With the obvious need for advanced nuclear power to meet changing electricity and energy demands, the technology today must develop and demonstrate advanced online monitoring techniques and begin to learn now how such tools can be used to support and improve decision making. One key aspect of this advanced technology is modeling how the unique characteristics of the nuclear industry supply chain impact resource availability and lead-times. This involves modeling the risk propagation behavior and its relationship on resource availability from suppliers and how the measurement of overall risk exposure can result in delays. To achieve this, this research begins by examining today's supply chain and the relationship between each participating actor in the network.

2.0 Supply Chain Modeling and System Dynamics

The need to model the supply chain is to generate synthetic data that relates to the functions and processes surrounding production, inventory positions, and how the flow of resources moves between different supply chain agents. The synthetic data is used to estimate the resource availability of upstream suppliers, providing likelihoods of supplier inventory levels, and the ability to extract information on back order rates. This data and their associated likelihoods are used in a risk-based decision making network.

To achieve this, the relationships between processes and supply chain agents are studied. Thereafter, their dynamics are considered through causal relationships between production and inventory environments. By identifying the flow of information and material in these environments, systems theory is employed as a modeling tool and state-space representation is formulated for inventory level-based systems and inventory order-based production systems. Finally, the state-space model is used to demonstrate how the bullwhip effect impacts the supply chain processes.

2.1 Block Diagrams for Supply Chain Dynamics

The supply chain consists of a number of different agents such as suppliers, manufacturers, and distributors. There are strong dependencies between the agents that determine how the flow of products, services, finances, and/or information moves and must be established to model the supply chain. The model must also take into account the internal processes enforced by each agent that are established by supply chain and inventory management. The design of the supply chain model begins by locating the agents and facilities in different tiers of the chain. Thereafter, the dependencies between each agent are evaluated by determining the directional flow of materials and information throughout. Once the relationship between agents is established, the characteristics of the manufacturing processes is developed for each agent in terms of their production-inventory scheme, all of which can be achieved using block diagrams.

Block diagrams stem system dynamics, which is the study of interactions between components and their environment [82]. The goal of the block diagram is to qualitatively represent the key elements that are important within the system under examination and to provide an understanding

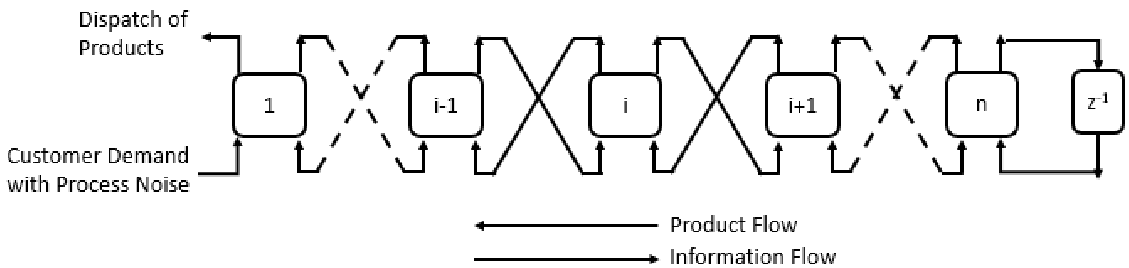


Figure 2.1: Simple multi-stage block diagram for a supply chain with n stages.

into the causal relationship between the key elements. Block diagrams have been employed to study the system dynamics of health care systems, pests and natural enemy interactions, and economic systems [56, 63, 77].

Within this framework, the supply chain modeling process is performed by creating a block diagram. The critical elements for a supply chain include identifying how information and products flow between agents and how this flow creates the structured network of interdependent causal links. The block diagram can be extended further to each agent by identifying their respective critical elements for manufacturing processes and inventory strategies. This can be achieved by examining the production-inventory strategies at the agent level.

In this research, simple multi-stage supply chain diagrams are developed to model how the flow of demand information and products within the supply chain impact inventory position [64]. This model is chosen to provide a simple relationship between agents and how information and resources flow between them. The model can be extended to have n general agents with i denoting the intermediate agent index. Each intermediate agent has a causal relationship between its neighboring stages with respect to its inventory position and incoming/outgoing products [65]. Figure 2.1 shows a generic multi-stage case.

This research includes an additional block diagram depicting the manufacturing processes and inventory strategies by studying how information and products flow within a supply chain agent. This encompassing review of the internal processes establishes functions and mechanisms that provide a more thorough model at the agent level. This model defines the production-inventory systems, which are integrated systems of inventory control policies and production processes [21, 83]. Figure 2.2 depicts a general production-inventory system as a block diagram. It should also be noted

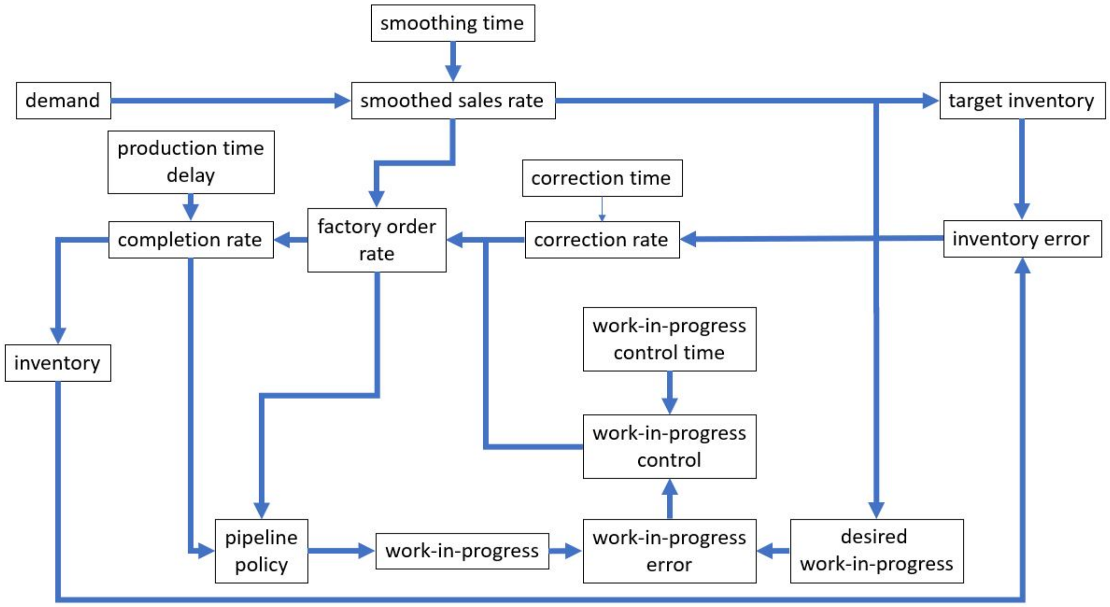


Figure 2.2: A block diagram for manufacturing processes.

that all the elements in the production-inventory block diagram system can be modified to represent any supply chain market[1].

The key elements in this block diagram represent the decisions made by supply chain and inventory management and how the flow of goods and information impact the order rate and inventory levels. For example, the input to the diagram is sales or incoming demand. This arrow from sales to smoothed sales rate shows the propagation of information as a positive feedback shown by the positive sign. In the smoothed sales rate, management makes a decision on an appropriate forecasting method. The arrows coming from the smoothed sales rate depict the impacted information by the forecasting method as they propagate through the diagram. If management chooses an effective forecasting method, then the order rate will align with production. There are additional control mechanisms that are chosen by the management in these systems, where depending on the input demand, the output of inventory or production can result in a stable or unstable response.

2.2 Control Theory and State-Space Representation

In order to model the dynamics of the control mechanisms studied from the proposed block diagram systems, control theory is employed. Systems and control theory is a branch of engineering for the purpose of developing a model or a governing function to drive a dynamical system to a desired state [26]. Control theory is a common tool in studying supply chain systems and production-inventory policies [50]. The theory enables the crucial evaluation of feedback systems and identification of causal relationship, which are common attributes in the supply chain.

Modeling in control theory makes use of the state of a system, which is a collection of variables that summarizes the past of a system for the purpose of predicting the future [5]. State variables are defined in the state vector $x \in \mathbb{R}^n$. The control variables are defined in the input vector $u \in \mathbb{R}^p$. The measured signal are defined in the output vector $y \in \mathbb{R}^q$. A system can then be defined by the following differential equation, which is a non-linear state-space representation:

$$\frac{dx}{dt} = f(x, u)y = h(x, u) \tag{2.1}$$

where $f : \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}^n$ and $h : \mathbb{R}^n \times \mathbb{R}^p \to \mathbb{R}^q$ are smooth mappings. The model in this form is defined as a state-space model. The model can be further simplified as a linear state-space representation:

$$\frac{dx}{dt} = Ax + Buy = Cx + Du \tag{2.2}$$

where A, B, C and D are constant matrices. The matrix A is defined as the dynamics matrix, the matrix B is defined as the control matrix, the matrix C is defined as the output matrix, and the matrix D is defined as the feedthrough matrix. State-space representation can be defined for both differential and difference equations. Further properties and derivations can be found in [5].

2.3 Multi-Stage Supply Chain State-Space Representation

Using the block diagrams illustrated in Figure 2.1, a state-space representation for the model can be formulated. The purpose of this model is to demonstrate the observed amplification of inventory position due to a sudden change in demand input. It is assumed that there is no delay time between resources being transported between supply chain agents and that no back-orders can accumulate.

Figure 2.1 shows a generic multi-stage, series supply chain with n stages, where each stage depicts a supplier chain agent. The inventory position of the supply chain agent i at time t is defined as $I_i(t)$ and is controlled with a proportional inventory-replenishment policy through the parameter k_i. In this model, the inventory-replenishment policy indicates that the inventory position is always trying to maintain a setpoint defined by inventory management. Additional details about the model can be found in [64].

The products to be delivered moves from right-to-left, indicating that the resources are flowing from agent, i, to its downstream agent, $i-1$, at time t. This resource flow relationship is defined as $Y_{i,i-1}(t)$. Additionally, the measured output for this relationship is inventory position for agent i with respect to time t. The inventory includes products still in transit and those that are currently held in inventory. This yields the inventory position, $IP(t)$, difference equation:

$$IP_i(t) = I_i(t-1) + Y_{i+1,i}(t) - Y_{i,i-1}(t) \tag{2.3}$$

The orders placed between supply chain agents moves from left-to-right, indicating that ordering information is flowing from agent, i, to its upstream agent, $i+1$, at time t. Additionally, the ordering dynamics includes the inventory-replenishment policy, which returns the inventory position to its desired setpoint after an order has been made. The dynamics in ordering products between agents is formulated in the following difference equation:

$$O_{i,i+1}(t) = k_i(SP_i - IP_i(t)) \tag{2.4}$$

where k_i is the inventory-replenishment gain factor for agent i and SP_i is the inventory target setpoint, which are chosen by inventory management to define their inventory-replenishment policy set by inventory management

Unfulfilled orders at each agent i is accounted for by introducing the standing orders variable $O_i^s(t)$. This variable defines the amount of orders to be processed by agent i at time $t+1$ through the following difference equation:

$$O_i^s(t) = O_{i-1,i}(t) + O_i^s(t-1) - Y_{i,i-1}(t) \tag{2.5}$$

To further simplify the model, it is assumed that each agent can satisfy demand, indicating that back-orders cannot accumulate, such that $Y_{i,i-1}(t) = O_i^s(t-1)$. This implies that the unfulfilled orders at the previous time step are counted for as the resources being transported.

Next consider the dynamics of one supply chain agent in this model. There are two inputs for each agent: incoming demand information ($IF_{i,I}$) and incoming resources ($R_{i,I}$). Each agent has two outputs: outgoing demand information ($IF_{i,O}$) and outgoing resources ($R_{i,O}$). There exits a relationship between the inputs and outputs such that $IF_{i,I} = IFi-1, O$ and $R_{i,I} = R_{i+1,O}$. The last agent is assumed to be a manufacturing agent producing raw materials, which is modeled as a time delay defined as ϕ. In state-space form, each agent can be represented as:

$$x_i(t+1) = A_i x_i(t) + B \begin{bmatrix} IF_{i,I} \\ R_{i,I} \end{bmatrix} y_i(t) = \begin{bmatrix} R_{i,O} \\ IF_{i,O} \end{bmatrix} = Cx_i(t) + D \begin{bmatrix} IF_{i,I} \\ R_{i,I} \end{bmatrix} \tag{2.6}$$

For the manufacturer producing raw materials, the state-space model is:

$$x_\Phi(t+1) = A_\Phi x_\Phi(t) + B_\Phi IF_{i+1,O} R_{i+1,I} = C_\Phi x_\Phi(t) \tag{2.7}$$

where $A_\Phi = 0$ and $B_\Phi = C_\Phi = 1$.

Let $x_i(t) = (IP_i(t-1) \;\; Y_{i,i-1}(t))'$, $IF_{i,I}(t) = O_{i-1,i}(t)$, $R_{i,I}(t) = Y_{i+1,i}(t)$, $R_{i,O}(t) = Y_{i,i-1}(t)$, and $IF_{i,O} = O_{i.i+1}(t)$. By setting $n = 3$ to represent a four-tier supply chain, including the raw material manufacturer, defines the following state-space:

$$
\begin{aligned}
A &= \begin{bmatrix} 1 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 1 \\ -k_1 & k_1 & 0 & -k_1 & 0 \\ 0 & 0 & -k_2 & k_2 & k_2 \end{bmatrix} \\
B &= \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ k_1 & 0 \\ 0 & k_2 \end{bmatrix} \\
C &= \begin{bmatrix} 0 & 0 & -k_2 & k_2 & -k_2 \end{bmatrix} \\
D &= 0
\end{aligned}
\tag{2.8}
$$

2.3.1 Bullwhip Effect Modeled as a Step Response for Multi-Stage Supply Chain

Uncertainty regarding incoming customer demand can lead to risks for any supply chain system [36]. A sudden change in demand is a key factor in the dynamics of supply chain modeling and often causes the phenomenon known as *the bullwhip effect.* The bullwhip effect typically starts with a sudden, unexpected increase in consumer demand. There has been a direct observation that the sudden increase in demand amplifies and propagates throughout the entire supply chain, causing extreme fluctuations in inventory and production environments [48]. The bullwhip effect is depicted in Figure 2.3. Such an effect propagates throughout the entire supply chain, impacting the inventory position of all agents, which can increase lead-times due to shortages or lost revenue due to excessive inventory [15].

The bullwhip effect can be analyzed by modelling the dynamics of the supply chain and how the behavior of goods and information flow between agents. As is done in this research, the dynamics and behaviors of the bullwhip effect are often modelled using a step response. By modeling sudden demand as step inputs to the models, the consequences of bullwhip can be observed as extreme fluctuations in their states and observed outputs [64].

For the multi-stage supply chain model, the bullwhip is observed by choosing the proportional gain that serves as a inventory-replenishment mechanism. For typical inventory position behavior

Figure 2.3: The bullwhip effect and its impact on the supply chain as shown by [48].

the gains were set to $k_1 = 0.8$ and $k_2 = 0.6$ and the desired setpoints for the inventory positions were *SP1* $= 100$ and *SP2* $= 750$ for supply chain *agent 1* and supply chain *agent 2*, respectively. These parameters are assumed only to illustrate the dynamics of the model and the behavior of inventory position. The model is simulated with a step input to depict incoming demand. The inventory position at *agent 1* is stable at its defined inventory position setpoint of 100 units. Similary, the inventory position at *agent 2* is stable at its defined inventory position setpoint of 750 units. Figure 2.4 shows the simulated results for 30 days.

For a bullwhip impacted inventory position, the gains were set to $k_1 = 1.8$ and $k_2 = 2.1$ and the desired setpoints were unchanged. These parameters are assumed only to illustrate the dynamics of the model and the behavior of inventory position when the inventory-replenishment gains are incorrectly chosen. The model is simulated with a step input to depict incoming demand. The inventory position at *agent 1* overshoots its defined inventory position setpoint of 100 units followed by large fluctuations until stabilization occurs at $SP1 = 100$. The inventory position at *agent 2* depicts an unstable inventory position with extreme fluctuations that increases beyond the setpoint at $SP2 = 750$. Figure 2.4 shows the simulated results for $t = 30$ days.

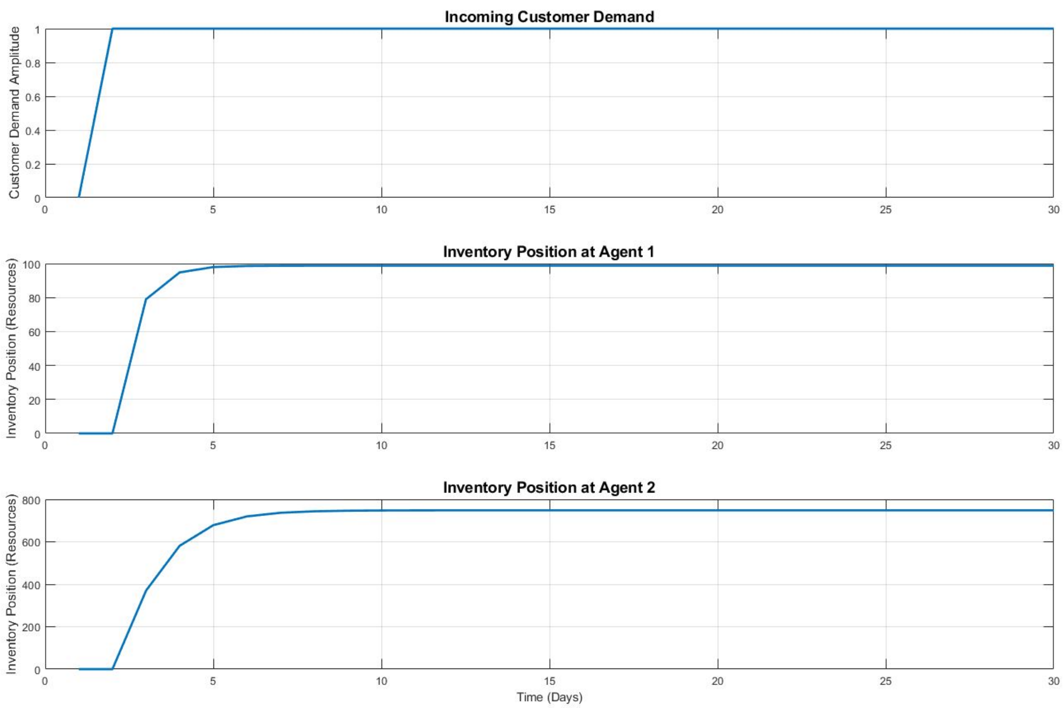


Figure 2.4: Typical inventory position behavior when the inventory-replenishment policy is appropriately set.

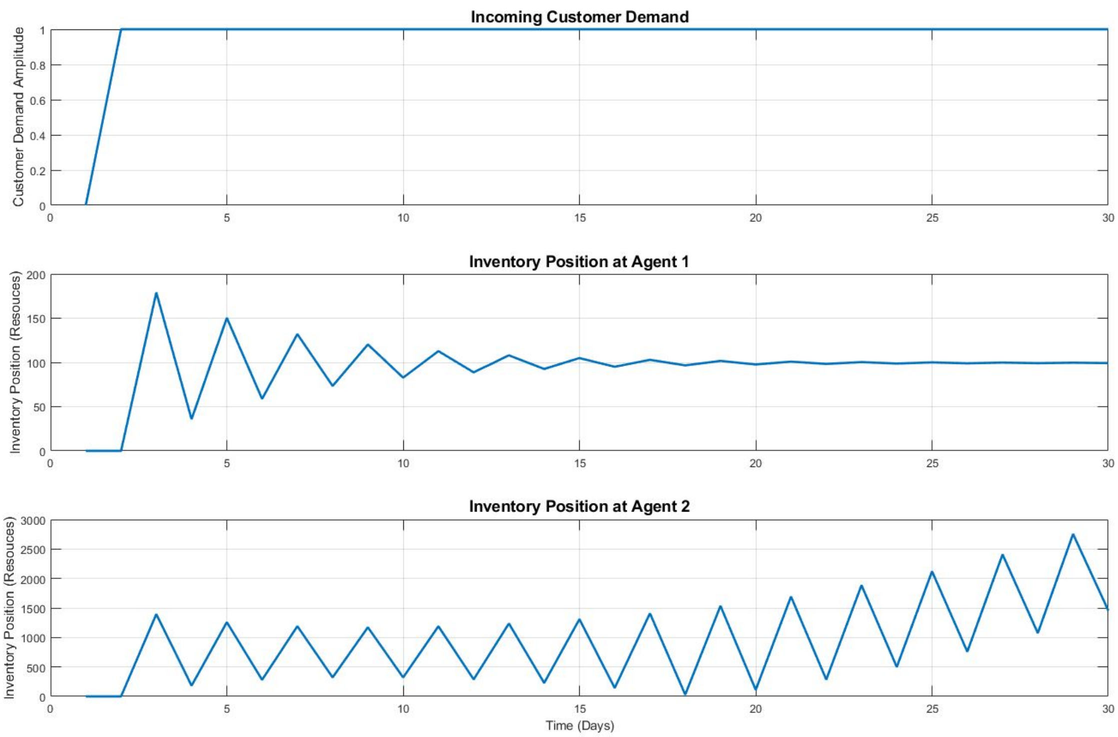
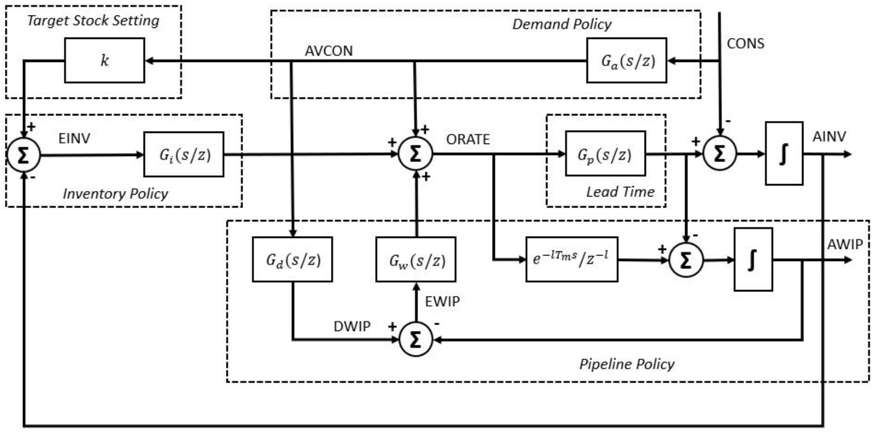


Figure 2.5: The bullwhip effect observed as amplified inventory positions.

2.4 Inventory Order-Based Production Control Systems

Advanced control laws with additional feedback loops for supply chain modelling has been investigated throughout the years, where the works of Towill [83] and Coyle [14] most notably introduced the inventory and order-based production control systems (IOBPCS). Its creation is based on the block diagram shown in Figure 2.2. The IOBPCS has evolved into a family with custom components and parameters depicting a general production and inventory control structure [51].

The IOBPCS has been described by several different formulations including differential/difference equations, state-space representation, and transfer functions in both the continuous and discrete domain [70]. The main components consist of an inventory policy (inventory feedback loop), pipeline policy (work-in-progress (WIP) loop), a desired stock setting, a lead-time, and a demand policy (forecasting setting). The IOBPCS structure in block diagram representation and its components are shown in Figure 2.6.



Abbrev.	Description
AINV	actual inventory
AVCON	average consumption
AWIP	actual work-in-progress
COMRATE	completion rate
CONS	market demand
DINV	desired inventory
DWIP	desired work-in-progress
EINV	error in inventory
EWIP	error in work-in-progress
ORATE	order rate

Figure 2.6: The block diagram for a generic IOBPCS and nomenclature.

Various systems from the family of IOBPCS can be modeled by tuning the following main components:

1. **Lead-Time:** the time between the initial order and when the product is settled into inventory. For manufacturing agents, lead time may include production delays or a production smoothing element and can be tuned according to the particular process in question i.e. MTO or MTS.
2. **Demand Policy:** the mechanism that represents a statistical forecasting task that averages the incoming demand. If the forecasting setting is chosen correctly, then the inventory will approach the required demand in the supply chain.
3. **Inventory Policy:** the feedback loop that controls the error between the actual inventory level and the desired inventory level.
4. **Pipeline Policy:** the work-in-progress (WIP) feedback loop that determines the error in WIP (EWIP) and refers to the inventory items that have yet to reach their final destination.
5. **Desired/Target Inventory:** the fixed inventory setting and, in some cases, the setting can be tuned to a multiple of current average sales rates [70].

2.4.1 IOBPCS Dynamics

The dynamics of the IOBPCS have two performance objectives [70]:

- inventory/resource level recovery
- reduce error in incoming demand on the ordering rate

These objectives are achieved through the design of the IOBPCS dynamics and can be observed when a step input is introduced as a sudden change to incoming demand. The response of the system is studied in terms of the system's inventory with respect to common control theory characteristics such as rise time, settling time, and maximum overshoot.

The designer of the system chooses the target stock level, the lead-time, and selects the three policies discussed in 2.4 in order to replicate the supply chain under investigation. Figure 2.6 shows the system with the policies in block diagram form. When the policies are tuned, different members of the IOBPCS family are derived in state-space representation. The dynamics of the target stock level, the lead time, demand policy, inventory policy, and pipeline policy are as follows:

1. **Target Stock Level:** The target stock level is defined by the parameter k and is a typical capacity limit in inventory management, which can also serve as a buffer stock.

2. **Lead-Time:** The lead-time is a fixed parameter, modeled using Padé approximations, that the designer cannot control but must be established in the model to represent the production lead-time of the system. The lead-time controller identifies the time, or delay, a resource is in production until it is finished and can be shipped to the customer. The continuous-time delay was introduced by Winker [89] as the following:

$$G_p(s) = \frac{1}{((T_p/n)s + 1)^n} \tag{2.9}$$

where $n = 1$ for a first-order delay, $n = 3$ for a third-order delay, and $n \to 8$ for an infinite order delay. The parameter T_p is defined as the average lead-time of the product in production for when $n = 1$ and $n = 3$. The parameter T_p is defined as a fixed lead-time when $n \to 8$. If the designer is to choose a fixed lead-time, then the dynamics for continuous-time and discrete-time are as follows:

$$\begin{aligned} \text{continuous-time: } G_p(s) &= e^{-T_p s} \\ \text{discrete-time: } G_p(z) &= z^{-q} \end{aligned} \tag{2.10}$$

where $T_p = qT_m$ and T_m is the sampling interval for the discrete-time dynamics.

3. **Demand Policy:** The dynamics of the demand policy attempts to measure the current or incoming market demand and aims to produce zero steady-state offsets with virtually no oscillatory transient responses in the output, AVCON. This is achieved by modeling the demand policy as an exponential weighted average process, which is commonly used in industry today [70]. The parameter, T_a, changes the sensitivity demand process and resembles a moving average that is defined by the following:

$$\begin{aligned} \text{continuous-time: } G_a(s) &= \frac{1}{T_a s + 1} \\ \text{discrete-time: } G_a(z) &= \frac{a}{1 - (1 - a)z^{-1}} \end{aligned} \tag{2.11}$$

where a in the discrete-time domain is defined as:

$$a = \frac{1}{(1 + (T_a/T_m))}. \tag{2.12}$$

Equation 2.11 is a standard exponential smoothing function. Other academics [19] proposed a linear or quadratic exponential smoothing forecasting technique. These forecasting techniques are defined in the continuous-domain by the following:

$$
\begin{aligned}
\text{Linear: } G_a(s) &= \frac{2T_a s + 1}{T_a^2 s^2 + 2T_a s + 1} \\
\text{Quadratic: } G_a(s) &= \frac{3T_a^2 s^2 + 3T_a s + 1}{T_a^3 s^3 + 3T_a^2 s^2 + 3T_a s + 1}
\end{aligned}
\tag{2.13}
$$

4. **Inventory Policy:** The dynamics of the inventory policy defines the rate at which the inventory replenishes through the T_i parameter. Ideally, if the inventory is low then the production system would want to replenish to the target inventory as soon as possible. The parameter adjusts the ORATE in the system, in other words, how quickly the inventory replenishes from the discrepancy between the target stock level and actual inventory (AINV). The inventory policy also takes into account the lead-time of the system because if the policy replenishes the inventory prior to the lead-time then oscillatory behavior will occur due to excessive work-in-progress (WIP). The dynamics can be modeled with a simple gain block with the following parameter:

$$
\begin{aligned}
\text{continuous-time: } G_i(s) &= \frac{1}{T_i} \\
\text{discrete-time: } G_i(z) &= \frac{1}{T_i}
\end{aligned}
\tag{2.14}
$$

5. **Pipeline Policy:** The dynamics of the pipeline policy attempts to correct and reduce the error between the desired work-in-progress (DWIP) and the actual work-in-progress (AWIP). The pipeline policy contains two parameters the designer can tune: T_w and T_p. The T_w parameter calculates the quantity that should be added to the orders by evaluating the error between the desired WIP and the actual WIP. The T_p parameter is associated with the lead-time mechanism and was discussed earlier in this section. In the pipeline policy, both parameters are modeled as gain blocks:

$$
\begin{aligned}
\text{continuous-time: } G_w(s) &= \frac{1}{T_w}, G_d(s) = T_p \\
\text{discrete-time: } G_w(z) &= \frac{1}{T_w}, G_d(z) = T_p
\end{aligned}
\tag{2.15}
$$

The IOBPCS block diagram depicted in Figure 2.6 contains one input, CONS, and two outputs, AINV and COMRATE. The input-output relationship defines the following transfer function in the continuous-domain:

$$
\begin{aligned}
\frac{\text{AINV}}{\text{CONS}} &= \frac{-T_i(T_aT_ps^2+(T_a+T_P)s}{(T_as+1)(T_iT_ps^2+T_is+1)} \\
\frac{\text{COMRATE}}{\text{CONS}} &= \frac{(T_a+T_i)s+1}{(T_as+1)(T_iT_ps^2+T_is+1)}
\end{aligned}
\tag{2.16}
$$

It should be noted that both transfer functions share the same third-order characteristic equation. Additionally, all of the coefficients are positive, which implies that the transfer functions are stable for all non-zero choices in the design of the IOBPCS parameters. The dynamics of the IOBPCS and its family has been extended to not only continuous-time transfer functions, but to discrete-time transfer functions, which can be found in various sources on the matter [88]. With the transfer functions, the state-space representation is derived for all flavors of the IOBPCS family. Their derivations and state-space representation can be found in [45].

The benefit of using the IOBPCS not only lies in its variety of flavors when tuning the parameters, but also in its ability to mimic specific supply chain strategies. The strategies discussed in the upcoming sections will show that there are make-to-order (MTO) and make-to-stock (MTS) processes, that contain their own functions as portrayed by their tuned policies. To this end, the IOBPCS family is employed to model the desired MTO/MTS supply chain.

2.4.2 Bullwhip Effect Modeled as a Step Response for Standard IOBPCS Model

The bullwhip effect can be analyzed by modelling the dynamics of the supply chain and how the behavior of goods and information flow between agents when uncertain demand patterns are introduced. In this research, the dynamics and behaviors are modelled by applying control theory applications to represent the common supply chain operations and policies. By introducing sudden demand inputs as step inputs into the IOBPCS model, the consequences of bullwhip can be observed through the outputs of the control system models as extreme fluctuations in the states of the model and its measured outputs [84].

The APVIOBPCS state-space from [45] is chosen for the simulation in order to show how policy configurations can lead to the bullwhip effect. The reason for choosing the APVIOBPCS is because this model supports the use of all policy components that include demand, inventory feedback, inventory target, work-in-progress feedback, and lead-time. The state-space representation for this model describing actual inventory output is shown in 2.17. The policies for a desired output and a bullwhip impacted output are listed in Table 2.1 and the resulting simulations are found in Figure 2.7 for typical behavior and Figure 2.8 for bullwhip impacted behavior.

$$
\begin{aligned}
A &= \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ \frac{T_a(T_w - T_i}{T_i T_w (1+T_a)} & \frac{T_i(1+2T_a) - T_w(T_a T_i + T_a + 1)}{T_i T_w (1+T_a)} & 2 - \frac{1}{1+T_a} - \frac{1}{T_w} \end{bmatrix} \\
B &= \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \\
C &= \begin{bmatrix} \frac{a+T_i}{T_i(1+T_a)} + \frac{1}{T_w} & \frac{T_a}{1+T_a} - \frac{1}{T_w} & -1 \end{bmatrix} \\
D &= 0
\end{aligned}
\tag{2.17}
$$

Table 2.1: Configuration of APVIOBPCS policies to simulated typical and bullwhip impacted processes.

Model	Configuration	T_i	T_p	T_w	T_a	a
APVIOBPCS	Typical	2/3	1	1	-0.3	10
	Bullwhip	2/5	1	1	1	10

The APVIOBPCS state-space model is simulated for 290 days to account for an average number of work days. The policies in the APVIOBPCS model are configured to depict a inventory-production process that can handle a sudden increase in demand. The resulting simulating shown in Figure 2.7 illustrates the with the correct policies chosen then the inventory and work-in-progress outputs can stabilize after an initial overshoot. The chosen policies demonstrate that the system is underdamped and further analysis can be performed to ensure a faster settling time.

The policies in the APVIOBPCS model are configured to depict a inventory-production process that undergoes a bullwhip phenomena when a sudden increase in demand is introduced. The resulting simulating shown in Figure 2.8 illustrates the with the incorrect policies chosen then the inventory and work-in-progress outputs will become unstable. This results in extreme fluctuations in inventory space and the work-in-progress to match the incoming demand.

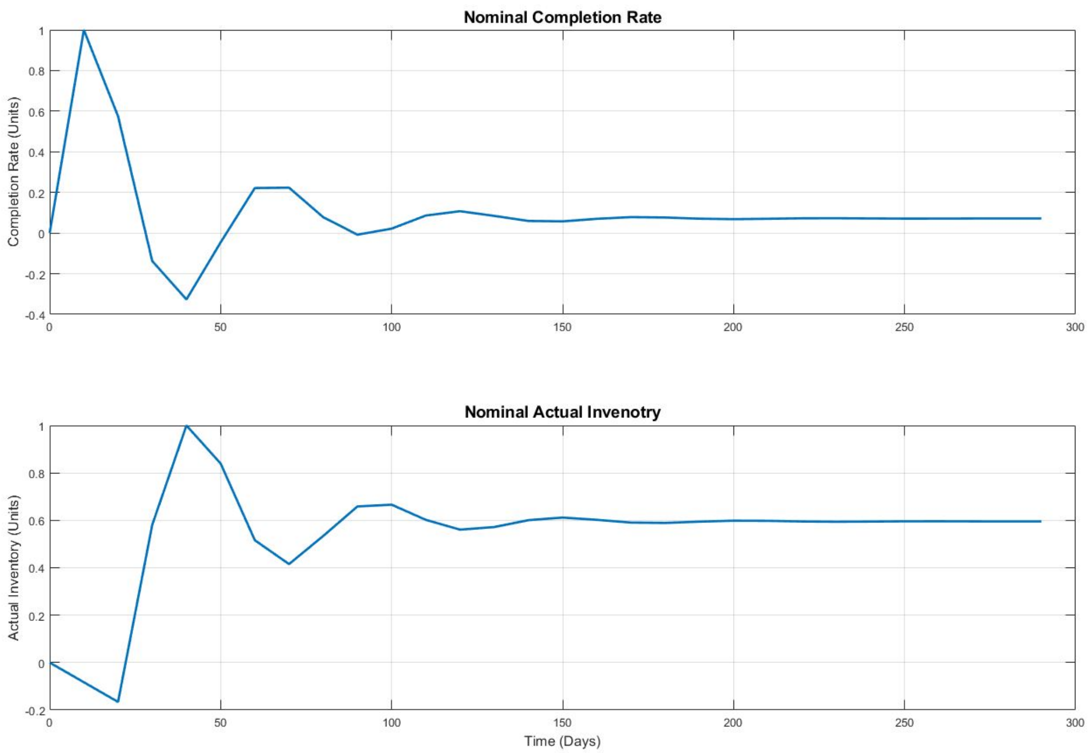


Figure 2.7: Typical behavior for APVIOBPCS showing a stable output of inventory and work-in-progress.

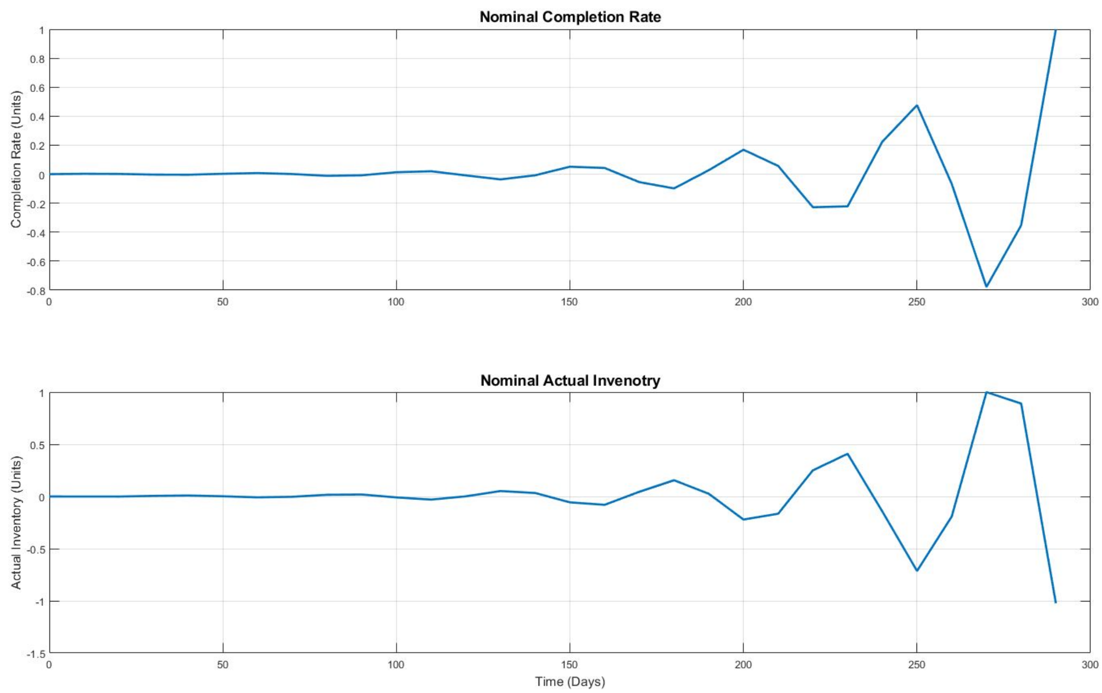


Figure 2.8: Bullwhip impacted behavior for APVIOBPCS showing an unstable output of inventory and work-in-progress.

2.5 Comparing Supply Chain Models

The multi-stage supply chain model and the IOBPCS model offer different dynamics and information when simulating the supply chain. The multi-stage supply chain has the freedom to be constructed with n stages. This results in a simple series supply chain identifies more as a supply chain network than the IOBPCS model since this represents a single agent in the supply chain. The multi-stage supply chain only offers one inventory policy and makes use of a number of assumptions when considering how products are delivered between agents and how this impacts the inventory level. The only parameter that is available to adjust in the multi-stage model is the inventory policy that acts as a gain for how much to replenish given the incoming demand.

On the other hand, the IOBPCS contains a number of adjustable parameters that depict the policies employed in the supply chain today. The IOBPCS policies have the ability to depict a number of scenarios that may cause issues in resource availability. If the demand policy is not set correct, as shown in the previous section, the average of incoming demand may not be able to maintain a steady state response given how the other policies are managed. Another example is if the work-in-progress parameter is not tuned correctly, which may simulate a case where the production is slowing due to an unforeseen error in machinery. Despite the IOBPCS model not being easily adaptable to represent multi-stage supply chain, it remains the best choice in modeling due to the dynamics of the policies and the scenarios that can represent their choices.

3.0 Supply Chain Strategies using Simple Inventory Models and the IOBPCS Model Family

Supply chains and their agents have inherent characteristics that define their manufacturing strategies [81]. These strategies are employed depending on how incoming demand impacts the start of production. The strategies can fall under three categories: (1) push-type, (2) pull-type, or (3) push/pull hybrid. The push-type strategy pushes resources that are driven by a forecast in demand, the pull-type initiates production through the pulling of customer demand, and the push/pull hybrid consists of a mixture of both characteristics.

The strategies are implemented in the supply chain model by defining the location of points that separate the forecast driven push-type demand from the customer driven pull-type demand known as the customer order decoupling point (CODP) [62]. The location of the CODP refers to where the customer no longer requires customization in its product. All activities upstream from the CODP are produced through traditional forecast demand methods and downstream activities are products pulled by the customer's demand.

An additional point is added to the models by recognizing that a customer rarely has access to its upstream supplier's data and can be identified by another decoupling point defined as the demand information decoupling point (DIDP) as investigated by [62]. The DIDP defines where a customer decouples from information flow leading to uncertainty in resource availability and capacity of upstream suppliers. This implies that if the location of the DIDP is immediately upstream to the customer, resulting in the customer's uncertainty surrounding resource availability increases.

In this chapter, the supply chain strategies and the location of the CODP and DIDP are integrated into the models developed in Chapter 2 to create a standard ship-to-stock (STS) supply chain and a make-to-order/make-to-stock hybrid supply chain. The uncertainty surrounding unknown orders being processed and other supply chain data due to the location of the DIDP is modeled by incorporating process and measurement noise to account for uncertainty in demand of upstream suppliers.

The first scenario, representing the STS market, uses the linear model described in Section 2.3. The scenario is described to represent a simple ship-to-stock supply chain where no customer customization exists in the supply chain. The purpose of this model is to demonstrate how the flow of information and resources in a supply impacts the inventory position of each supplier.

The second scenario uses the IOBPCS model described in Section 2.4 to represent a low-volume, high-value (LVHV) supply chain. Low-volume, high-value supply chains consists of highly customizable products [33], implying that the CODP location exists between supply chain agents. Two IOBPCS systems are placed in series with the CODP located in between, thus categorizing the first supply chain agent as a make-to-order (MTO) process since the customer is pulling the demand through the product's high levels of customization. The remaining supply chain agents upstream from the CODP contain a push manufacturing process or a make-to-stock (MTS) process. Thereafter, the mechanisms and policies within the IOBPCS systems are tuned to depict the MTO and MTS systems to produce a final model of a LVHV supply chain. Finally, inventory position and production-based states are observed by having both models undergo an input step demand, whose response will result in a stable response. Then, an unstable response in inventory position and production-based states is generated by introducing a sudden step demand that the supply chain cannot control, resulting in extreme, amplified fluctuations.

3.1 Demand Strategies and Customer Decoupling Point Thinking

Supply chain strategies can fall under three types of systems: (1) push-type, (2) pull-type, or (3) push/pull hybrid. The push-type implies a supply chain whose decisions regarding production is anticipated by consumer demand while a pull-type is driven by actual consumer demand [81]. A high-level illustration of these strategies is shown in Figure 3.1. The blue arrows from the customer imply that demand is being pulled by the customer and the red arrows starting from the factor imply that the resources are being pushed by anticipated customer demand at the end retail customer.

The push- and pull-type systems are further categorized by a range according to the customization or standardization of the manufacturing process of the product as shown by Figure 3.2. As one moves to the left, the manufacturing process produces more customized products, defining the system as a pull-type since the customer is pulling the demand through higher levels of customization. On the other extreme, moving to the right transforms the manufacturing process into producing a standardized product where push-type systems push demand for basic and standardized resources.

The types of systems depend on the location of the customer order decoupling point (CODP) as indicated by the dashed-lines in Figure 3.2. The CODP refers to where the customer no longer

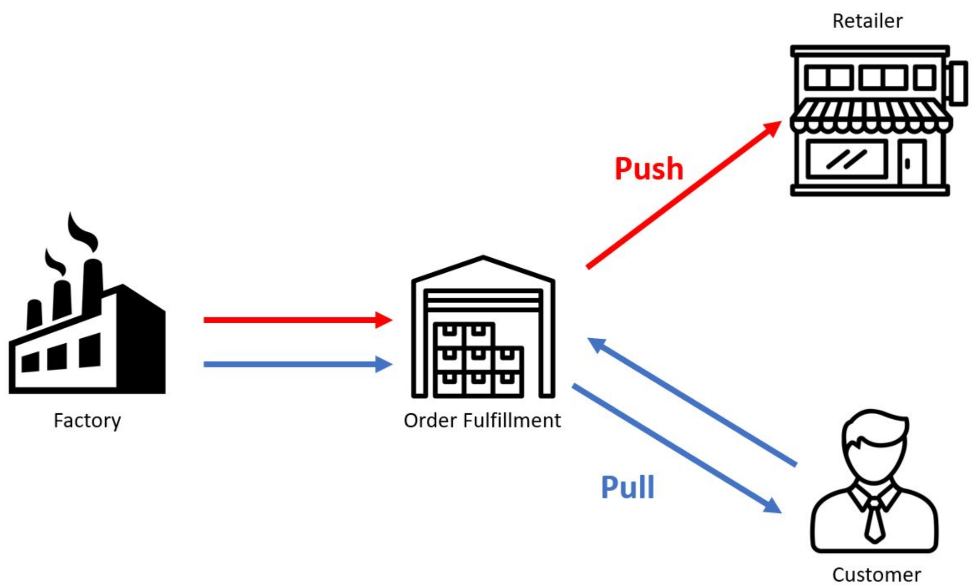


Figure 3.1: Supply chain strategies indicated by push or pull type demands.

requires customization in its product [27]. All activities upstream from the CODP are produced through traditional forecast demand methods, or push-type production, and downstream activities are products pulled by the true customer demand. The CODP is an important concept in structuring and configuring supply chains to ensure the end customer receives its desired product. The locations of the CODP requires an acute understanding of the market, its production properties, and its ancillary processes [62]. Ultimately, the CODP indicates where the organisation or the supply chain switches from a forecast driven production system and starts producing directly to a customer order [91].

As the desired product becomes more customizable, the manufacturing process moves towards rngineering-to-order (ETO), seen as moving left in Figure 3.2. At the ETO level, the production is a pure pull-type supply chain because production is being pulled by a customer requiring a product that is tailored to fit their own unique market. This is indicated by the CODP being located prior to the design block.

On the other extreme, as the desired product becomes more standardized, the manufacturing process moves to the right towards ship-to-stock (STS), becoming a push-type supply chain since production is pushed by forecasting methods. For STS, the CODP is located after the distribution block indicating that the supply chain for this product was driven by purely forecasting demand and standardized activities.

When modeling the supply chain, the CODP must be considered when identifying the market because it determines the functions and dynamics of the manufacturing process. For this research, two CODP strategies were chosen to develop two supply chain models: (1) supply chain that consists of three suppliers in series that identify with the STS systems, indicating that the CODP lies on the right side of Figure 3.2 and (2) supply chain that consists of a make-to-order (MTO), make-to-stock (MTS) hybrid where the CODP lies between the MTO and MTS series. After the CODP is established, the flow of resources and their interdependent relationships are studied in each system to determine system dynamics. The basis for choosing model (1) is to establish a simple linear model for how resources are shipped and received and to study how state-estimation techniques can be used for resource estimation of upstream suppliers. The basis for choosing model (2) is to establish a model depicting a LVHV supply chain with nonlinear capacity constraints due to their vulnerabilities and limited supplier selection.

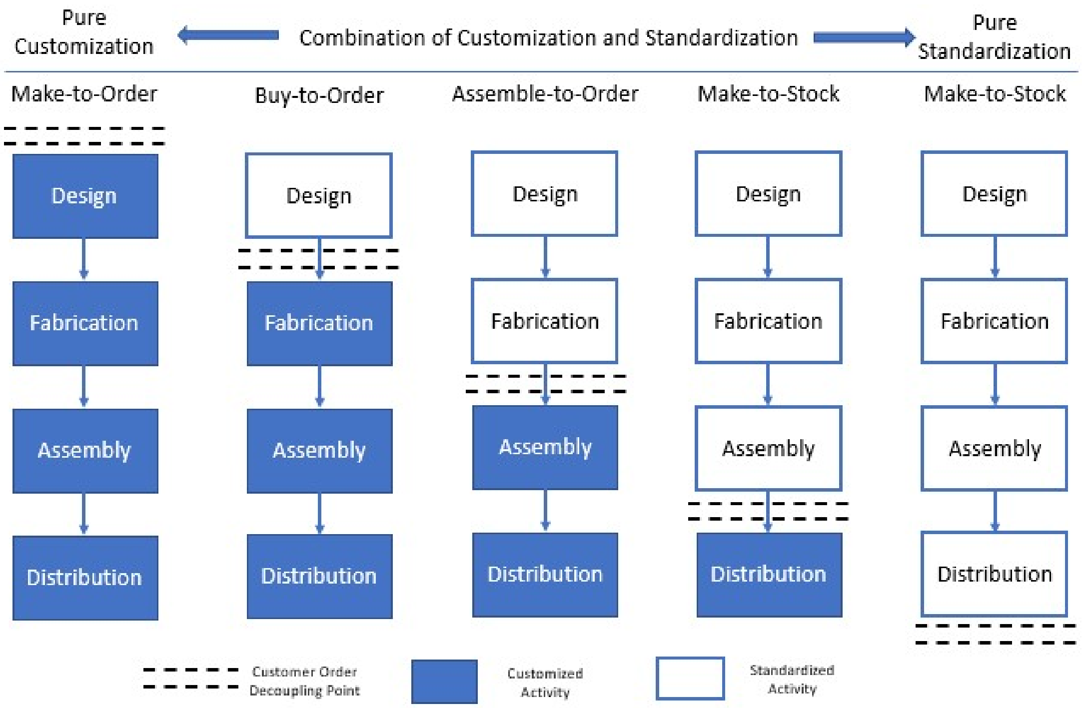


Figure 3.2: Different supply chain structures based on the location of the CODP.

3.2 Scenario 1: Inventory Position Model with Process and Measurement Noise

Consider the simple, three-tier series supply chain in Figure 3.3. It is assumed that the CODP is located at the beginning of the series network thus defining the entire model as ship-to-stock. For this research, the goods and resources in the STS system are shipped directly to the stock of the neighboring supply chain agents. This assumption implies that all manufacturing steps, such as design, fabrication, and assembly, have already been performed.

Further, the DIDP is located immediately upstream from the customers demand indicating that information regarding demand is not shared among the agents in the supply chain. With the addition of the DIDP at this location, process noise is summed with the input. This produces an uncertainty about the demand information, which includes uncertainty of incoming orders from other customers. The process noise is propagated into the model to account for how the uncertainty of demand impacts the inventory levels of upstream suppliers.

The model is developed using state-space representation and the derivation of the dynamics for the multi-stage supply chain can be found in Section 2. To simplify the model, the setpoint levels for the inventory levels are assumed to be constant and that the inventory replenishment policy is continuous through the proportional parameters k_1 and k_2. This implies that inventory management is reviewing its stock at each time step and is replenishing its stock if below the desired setpoint. Additionally, the number of resources at the manufacturing agent is assumed to be infinite indicating that the inventory can never be fully depleted.

Process and measurement noise are added to Equation 3.1 to account for uncertainty in inventory as w_k and v_k, respectively. The model used for synthetic data generation then becomes:

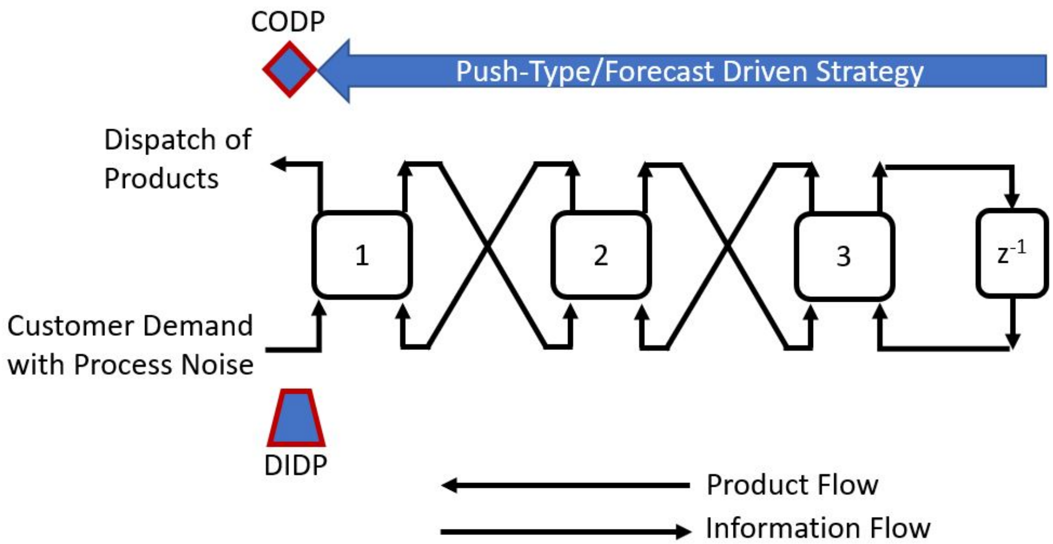


Figure 3.3: Simple multi-stage causal diagram for a three-tier supply chain.

$$
\begin{aligned}
A &= \begin{bmatrix} 1 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 1 \\ -k_1 & k_1 & 0 & -k_1 & 0 \\ 0 & 0 & -k_2 & k_2 & k_2 \end{bmatrix} \\
B &= \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ k_1 & 0 \\ 0 & k_2 \end{bmatrix} \\
C &= \begin{bmatrix} 0 & 0 & -k_2 & k_2 & -k_2 \end{bmatrix} \\
D &= 0
\end{aligned}
\tag{3.1}
$$

3.2.1 Synthetic Data for Typical and Bullwhip Inventory Position

The step response of the model described by Equation 3.1 generated the data for inventory position. The step input was used to depict incoming demand into the supply chain model. In order to observe a stable inventory response, hereafter defined as healthy inventory levels, and a bullwhip, unstable response the parameters were tuned to the values found in Table 3.1.

Table 3.1: Series supply chain parameters chosen for healthy and bullwhip impacted inventory positions.

	k_1	k_2	SP_1	SP_2
Healthy	0.8	0.6	100	750
Bullwhip	1.99	0.4	100	750

The data is successfully generated into two sets: (1) healthy inventory position data set and (2) bullwhip impacted inventory position data set. The healthy data set, shown in Figure 3.4, is simulated for 104 days. Since the uncertainty is introduced into the demand input, the inventory position of both suppliers parallel the fluctuations. Both suppliers satisfy the incoming demand as time steps forward with an averaged position at their desired setpoint, which is indicated by the red line in the figure.

This implies that the supply chain is under typical operating conditions and that resources are readily available to satisfy incoming customer demand.

The bullwhip data, shown in Figure 3.5, is extended to 300 days to highlight the bullwhip effect on inventory position. The bullwhip effect is observed as an amplified inventory position at both suppliers, which exceeds beyond the desired setpoint. The bullwhip effect causes extreme fluctuations in inventory position, indicating that the inventory replenishment policies for those suppliers is overwhelmed by the incoming demand. Consequentially, the amplified data implies that resources may not be readily available to satisfy incoming demand due to the saturating effects on inventory position as it amplifies far beyond the red lined setpoint in the figure.

Figure 3.4: Synthetic Data for a Healthy Inventory Position in Response to Customer Demand.

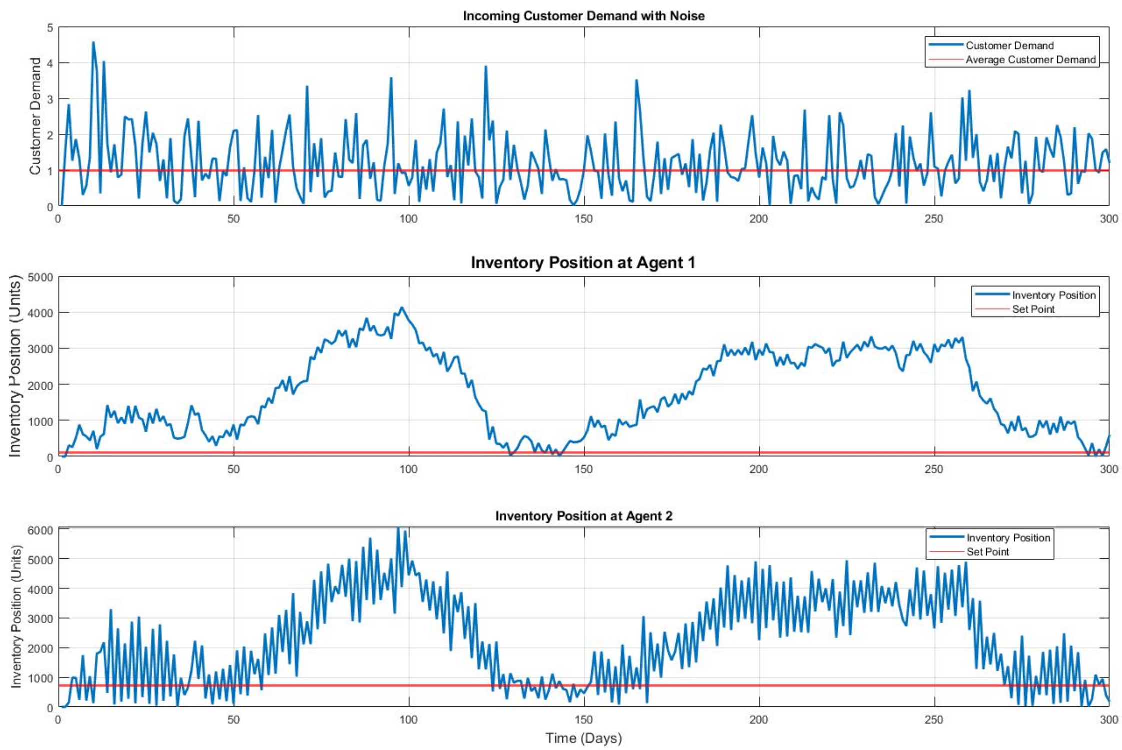


Figure 3.5: Synthetic Data for a Bullwhip Impacted Inventory Position in Response to Customer Demand.

3.3 Scenario 2: Low-Volume, High-Value Products

Low-volume, high-value (LVHV) products typically contain the following characteristics that define their supply chain and manufacturing processes: high levels of customization, demand for unique industrial processes, and often little-to-no suppliers that meet the customer's requirements [74]. These characteristics are sensitive to disruptions from upstream suppliers since the supplier of the LVHV product does not have inventory buffers or a lack of resources to accommodate for late deliveries [73]. Some examples of these supply chains include products developed for the aerospace industry, nuclear power plant construction, energy exploration, and shipbuilding [20, 46, 57].

One method to define LVHV supply chains is through decoupling thinking. The location of the CODP categorizes the immediate supply chain agent as a make-to-order (MTO) process since the customer is pulling the demand through the product's high levels of customization [89]. The supply chain does not end with this agent; it extends upstream to several suppliers and manufacturers. Those supply chain agents upstream from the CODP point are considered to be forecast driven and are categorized as make-to-stock (MTS) processes since the customer does not customize those resources. Therefore, the LVHV supply chain exists in a hybrid MTO/MTS environment whose dynamics consist of both a customer demand process and a forecast demand process.

With LVHV supply chains defined as a hybrid MTO/MTS environment, the system dynamics can be developed using the IOBPCS model discussed in Section 2.4. First, a general MTO model is developed using the IOBPCS model to depict the pull-type process. Thereafter, a general MTS model using the same methodology is developed to depict the push-type process. Once both models are formulated, the MTO model is integrated to the MTS model where the input of the MTS model is the output demand rate of the MTO model. The overall input of the hybrid model is the initial customer demand for the LVHV product and the output can be defined as the completion rate of the LVHV product.

3.3.1 Make-to-Stock Supply Chain Model

Push-type processes are those supply chain agents whose production depends on forecasting methods to account for incoming demand [42]. The forecast demand dictates the production and inventory schemes to satisfy the demand. These systems typically represent make-to-stock (MTS) systems since the products require little-to-no customer customization effort. A general MTS system is depicted in Figure 3.6. The MTS system operates similar to the standard IOBPCS dynamics discussed in Section 2.4 with the addition of some logic to include back orders. The system responds to the demand rate $\mathrm{DRATE}_{\mathrm{MTS}}$ and if there is no inventory for delivery, then back orders begin to accumulate.

The MTS system contains two main management parameters that can be adjusted to contain both linear or nonlinear elements: the back order management parameter, A, and the inventory management parameter, B. For the system to be linear the dynamics require that no back orders can accumulate and that the system will always satisfy incoming demand with available inventory.

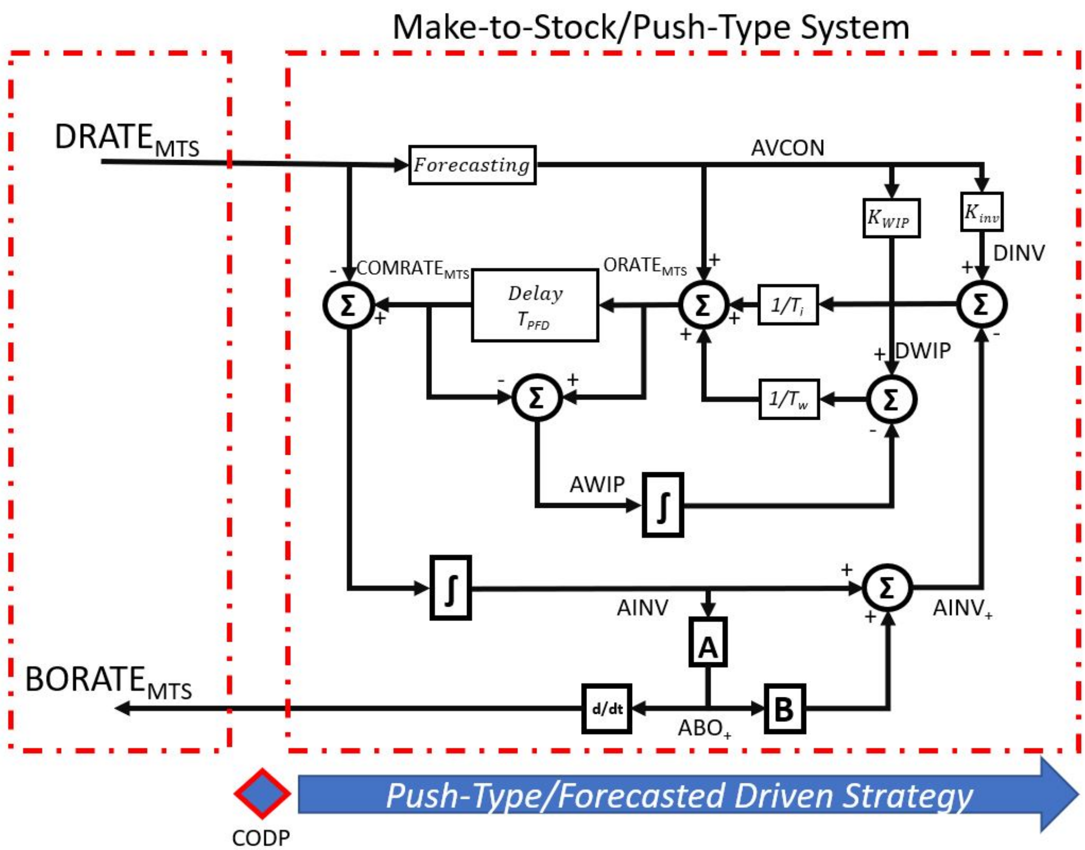


Figure 3.6: Make-to-Stock Diagram.

In order to materialize the linear MTS model, the back order management parameter is set to zero, $A = 0$, to turn off the logic that accounts for back orders.

A better representation of the real world system is to include back orders by creating a nonlinear model. This implies that the available inventory in the MTS system is finite. Including back orders allows actual inventory to be less than zero, AINV < 0, to account for the delay in production and back orders accumulating. The additional logic of the back order management must distinguish when there is excess inventory or when back orders start to accumulate. To do so, the nonlinear model requires that the A block in the system becomes

$$A = -\min(\text{AINV}, 0), \tag{3.2}$$

which diverts the positive inventory from the accumulating back orders as shown by the diverging logic in Figure 3.6.

The inventory management can be turned off or on by setting $B = 0$ or $B = 1$, respectively. When the inventory management is set to $B = 0$ in the nonlinear setting, then AINV_+ and ABO_+ can never be negative and the negative values of AINV are propagated to the calculation of $\text{ORATE}_{\text{MTS}}$. When the inventory management is set to $B = 1$ in the nonlinear setting, then the negative inventory values are accounted for in the production system.

In summary, with the B block set to either $B = 0$ or $B = 1$, two properties of the system can be obtained:

- Infinite material: no back orders with $A = 0$.
- Finite material: back orders are enabled with $A = -\min(\text{AINV}, 0)$.

where the finite material option implies that if the output of the system, $\text{BORATE}_{\text{MTS}}$, is positive then the $\text{DRATE}_{\text{MTS}}$ cannot be satisfied because back orders are increasing to only partially fulfill the demand. When the finite material option is enabled, then the system has no capacity constraints and the inventory will satisfy the incoming demand.

3.3.2 Make-to-Order Supply Chain Model

Supply chains in complex make-to-order (MTO) environments operate under different constraints and conditions than those in high-volume make-to-stock (MTS) structures. The IOBPCS models used to create the MTS supply chain is updated to meet a unique single project. This is achieved by transforming the inventory of the IOBPCS model to an order book system. The inventory of the IOBPCS model now depicts the error between the demand rate and the completion rate to represent an order book status. Because of this, the IOBPCS model no longer focuses on inventory but rather capacity, where [90] defines these systems as capacity and order based production control systems (COBPCS).

The IOBPCS model is updated to contain no feedback indicating an error in inventory to further identify the model as a COBPCS. In this system, the MTO is capacity driven by taking into account the actual order book variable, ABO. The ABO contains all customer orders received but not yet delivered. The MTO system also introduces a backlog variable, BL, which contains all customer orders that have been received but not yet released to production. The MTO supply chain system is shown in Figure 3.7.

There are two delays within the system that define the business lead-time and the production lead-time. The business lead-time defines the delay from when the customer has requested an order with engineering specifications for their product to when the capacity is allocated. The production lead-time is the delay for the entire production process of the requested good.

The MTO system contains two management parameter blocks: the capacity management C and the backlog management D. The capacity management block represents a lag strategy, which is when a manufacturer responds directly to an increase in demand then increases capacity to account for the change. The backlog management block represents how the backlog is handled by the system from a capacity perspective, which defines whether capacity is added to handle the increase in backlog orders.

The MTO system can represent a linear or nonlinear model by defining an infinite or finite capacity through manipulation of the C and D blocks. For the linear case, C can be set to unity to indicate that the available capacity, CAPRATE, matches the incoming demand of $\mathrm{DRATE}_{\mathrm{MTO}}$. The backlog strategy is modelled as a linear system by having the fraction $1/T_{\mathrm{BL}}$ be added to the capacity available based on available storage. Finally, based on the backlog management the orders in the system are handled in two ways:

- If $D = 0$ the backlogged orders are added to the new customer orders.
- If $D = 1$ then the additional capacity is added to the order rate to handle the backlog.

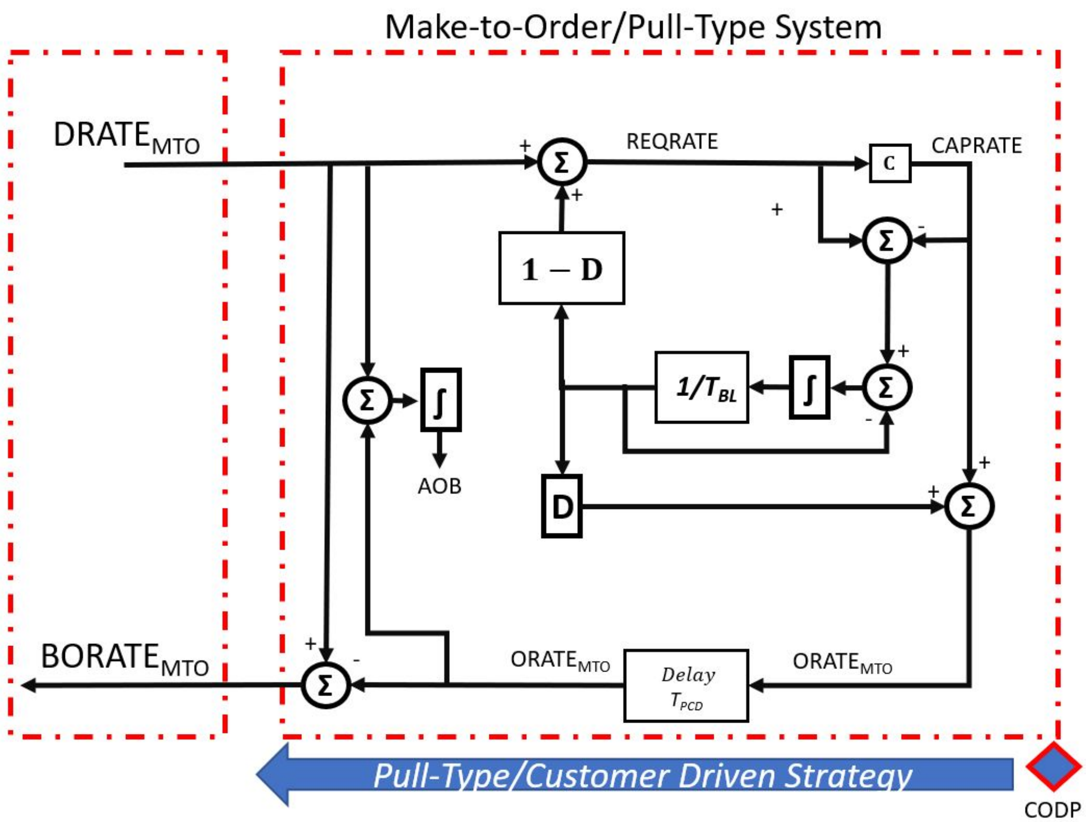


Figure 3.7: Make-to-Order Customer Driven System.

For the nonlinear model, the capacity management block is modelled by setting a limited CAPRATE, which is achieved by introducing a limited capacity constraint, CAPCON, and applying a first-order delay to the REQRATE. This yields the following equation:

$$\text{CAPRATE} = \min(\text{CAPCON}, \text{Smoothed}(\text{REQRATE}), \text{REQRATE}) \tag{3.3}$$

This implies that either CAPCON or Smoothed(REQRATE) may limit CAPRATE. If capacity is finite without the ability to increase capacity to account for orders in the backlog, then the quantity in the backlog is summed with the $DRATE_{MTO}$ with $D = 0$. If capacity has the capability to be increased to accommodate additional orders in the backlog, then that quantity is added to the order rate, $\text{ORATE}_{\text{MTO}}$ as is the case in the linear model by setting $D = 1$.

In summary, there are two different models defining the capacity of the MTO system:

- Infinite capacity: No capacity limit is used and $C = 1$ implying that all orders are delivered within the production lead-time CAPRATE = REQRATE.
- Finite capacity: Capacity of the system is finite when $C = \min(\text{CAPCON}, \text{Smoothed}(\text{REQRATE}), \text{REQRATE}$ where CAPCON is the maximum capacity available and no additional capacity is allocated to cover for the backlog e.g. $D = 0$.

3.3.3 Modeling the MTS/MTO Hybrid System for LVHV Products

For the LVHV scenario, the customer places an order for a highly customized product, which the MTO supplier allocates space for in their inventory and adds its productions to the order book. In order to produce the customized product, the MTO demands resources from its upstream supplier, whose production strategy consists of a forecast demand MTS process. Within the MTS process, the demand dictates the pipeline of production in order to provide the downstream MTO supplier its requested resources. Once the MTS has finished goods in their inventory, they are shipped to the MTO system to finalize the order book.

It is evident that the MTS/MTO hybrid model is a combination of the MTS and MTO system previously described. The two systems work as two separate entities from a supply perspective except for when insufficient inventory is available i.e. backorders in the MTS system start to accumulate which then impacts the amount of goods the MTO system receives. The integrated MTS/MTO hybrid system is shown in Figure 3.8.

It should be noted that the dynamics of the hybrid system show that when BORATE_{MTS} is positive this represents a growing ABO_{+}. The increasing ABO_{+} indicates that the delivery of finished goods has not satisfied the requested $\text{DRATE}_{\text{MTS}}$. This in turn reduces the $\text{ORATE}_{\text{MTO}}$ thus resulting in an unbalanced order book. Conversely, if the $\text{BORATE}_{\text{MTS}}$ is negative then ABO_{+} is reducing. This implies that the deliveries are reaching a stable state with respect to the requested $\text{DRATE}_{\text{MTS}}$. When this occurs the backorders are recovering thus the MTO system can satisfy its order book.

The availability of demand information is applied to the MTO/MTS hybrid through decoupling thinking as represented by the position of the demand information decoupling point (DIDP). Demand information defines the information about true sales, which is represented by the demand rate related to customer orders $\text{DRATE}_{\text{MTS}}$.

For the MTO/MTS hybrid, there are two possible positions for the DIDP: limited demand transparency or full demand transparency. For limited demand transparency, the DIDP is positioned after the MTS system and before the MTO system as shown in Figure 3.8. The DIDP is positioned in between the systems indicating that all the information from the customer orders dictates the MTO system and the MTS system is driven by forecast methods of the expected demand.

Full demand transparency occurs when demand information is shared to upstream agents to improve the forecasting methods employed in the MTS system. The DIDP is positioned upstream of both the MTO and MTS system. The overall system then extends the input demand information from the MTO system to the MTS input of the demand forecast block to account for full demand transparency. This change in control logic is accounted for in Figure 3.9.

3.3.4 State-space Representation of the Nonlinear LVHV System

Prior to defining the state-space model for the MTO/MTS hybrid system, there are several parameters that must be initialized. In this scenario, the MTO/MTS hybrid system takes on the perspective of LVHV supply chain where the MTO supplier manufactures complex products that are dependent on suppliers from a MTS supplier. For the purpose of this research, the MTO supplier is assumed to have no issues with incoming demand and has no orders moving to their backlog.

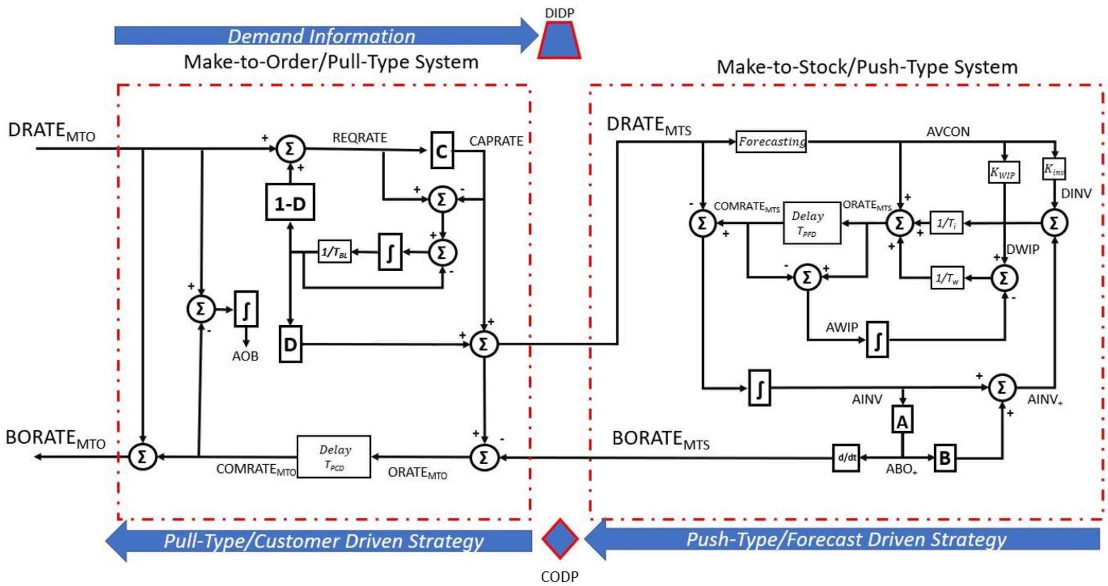


Figure 3.8: Integrated MTS and MTO system with limited demand transparency logic.

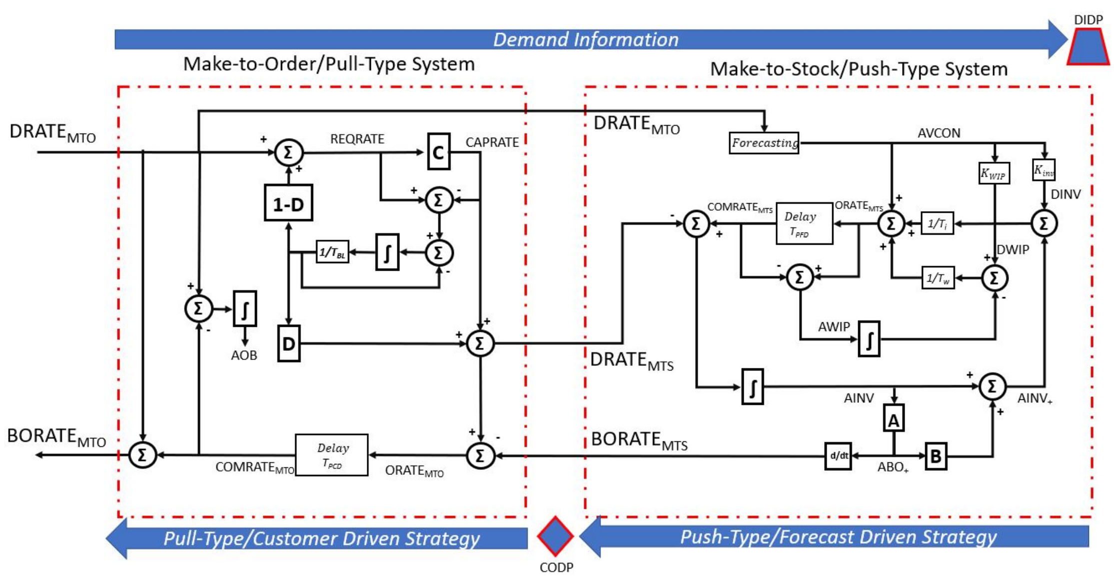


Figure 3.9: Integrated MTS and MTO system with full demand transparency logic.

This research assumes that the issues in this supply chain occur in the upstream MTS supplier, where in one case the MTS supplier is able to keep up with the orders from the MTO supplier and the other case depicts a MTS supplier whose backorder rate accumulates thus failing to ship the requested products to the MTO supplier.

All real-world systems, including inventory-based production and capacity-based production systems, are nonlinear. Therefore, the MTO/MTS hybrid system will contain the following non-linear elements defined by the MTO/MTS structure:

$A = -\min(\mathrm{AINV}, 0)$, $B = 1$ for backorder management.

C = $\min(\mathrm{CAPCON}, \mathrm{Smoothed}(\mathrm{REQRATE}), \mathrm{REQRATE})$ for capacity management.

$D = 0$ for Backlog management.

For the LVHV system, the nonlinearity comes from the capacity constraint, which can be likened to a saturation element that limits the inventory. This resembles real-world constraints because supply chain agents are limited to their physical warehouse space [60].

The MTO system is modeled to contain a lead-time of 32 weeks to account for the time to manufacturer complex LVHV products, while the MTS system has a lead-time of production of 4 weeks [24]. The remaining MTO parameters are chosen to ensure that no products are moved to the backlog. The parameters for the MTS system are chosen to model a system that satisfy the incoming demand from the MTO system, which are listed in the Healthy row in Table 3.2. The MTS model parameters are also chosen to depict a supplier that fails to appropriately allocate work-in-progress processes to account the demand, resulting in a positive back order rate and failure to deliver the requested parts to the MTO system. These parameters are listed in the Bullwhip row of Table 3.2.

With the LVHV established as a nonlinear MTO/MTS hybrid model, the state-space representation is developed by following the block diagram model shown in Figure 3.8. The state-space equations as represented by difference equations are listed in Appendix A with the addition of process and measurement noise to account for fluctuations and uncertainty in the system.

3.3.5 Synthetic Data for Typical and Bullwhip MTO/MTS Hybrid Models

Data is successfully generated for 52 weeks. The incoming demand is set to 50 units, which is reflected by the top graph in Figure 3.10 as Incoming Demand to MTO system. The states of the system that are most crucial are those plots titled Actual Inventory of MTS System and Actual

Table 3.2: MTS and MTO parameters chosen for nonlinear LVHV system to generate healthy and bullwhip data.

	Make-to-Stock (MTS)							
	A	B	T_A	T_{PFD}	T_I	T_W	K_{INV}	K_{WIP}
Healthy	$-\min(\text{AINV}, 0)$	1	20	4	1	2	8	4
Bullwhip	$-\min(\text{AINV}, 0)$	1	20	2	0.001	0.005	2	2

	Make-to-Order (MTO)					
	C	D	T_C	T_{PCD}	T_{BO}	CAPCON
Healthy	$\min(\text{CAPCON}, \text{Smoothed}(\text{REQRATE}), \text{REQRATE})$	0	2	32	4	100
Bullwhip	$\min(\text{CAPCON}, \text{Smoothed}(\text{REQRATE}), \text{REQRATE})$	0	2	32	4	100

Back Order of MTS System. These states indicate whether the MTS system has the capability to ship the requested products to the downstream MTO system. In Figure 3.10 the generated data shows that the system has the ability to satisfy orders by maintaining a zero back order rate after an initial transient of the incoming demand. This behavior is further reinforced by the actual inventory of the MTS system increasing as time steps forward.

The bullwhip impacted data is illustrated by identifying a positive non-zero back order rate in the MTS system. Figure 3.11 reflects the non-zero back order rate whose MTS system parameters cannot satisfy incoming demand, leading to a saturation inventory. Since the MTS system has inventory issues with capacity constrains then the order book of the MTO system cannot be fulfilled as would be the case in a LVHV scenario thus leading to delays with a lagging completion rate.

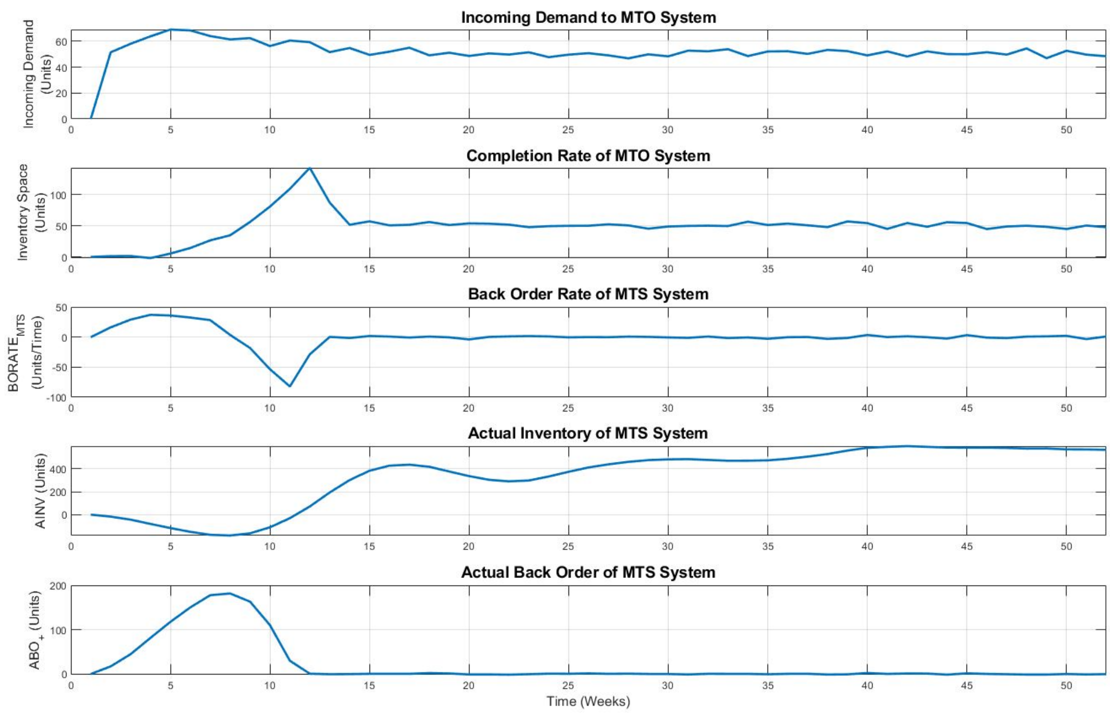


Figure 3.10: Synthetic data for a healthy LVHV system in response to customer demand.

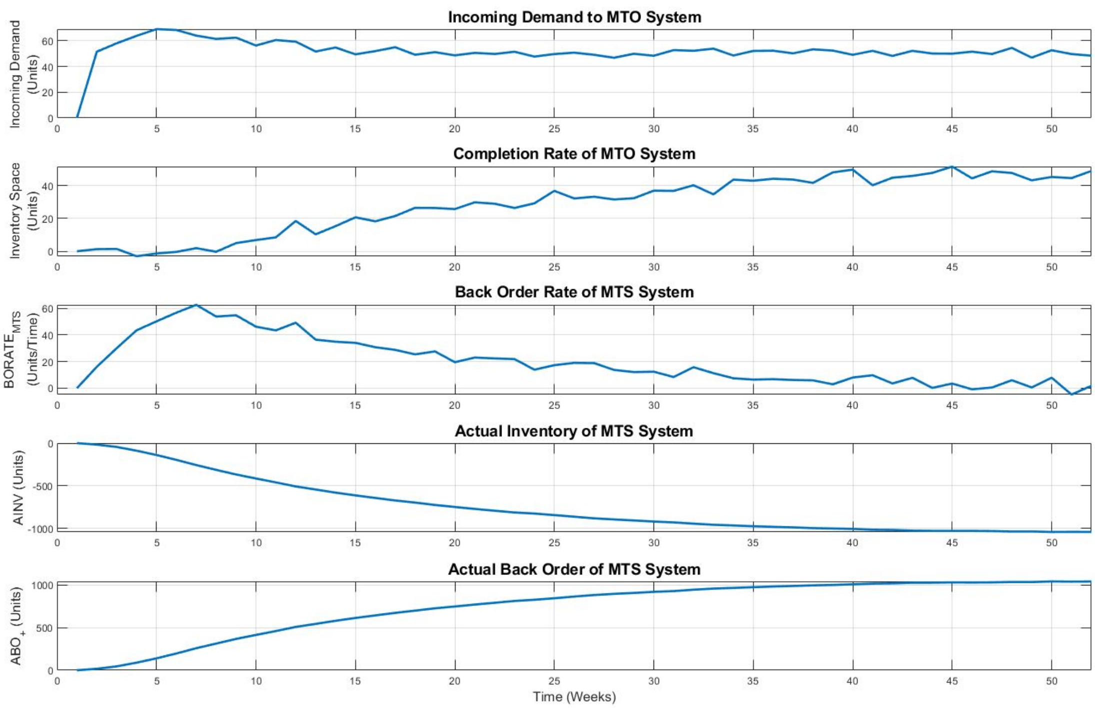


Figure 3.11: Synthetic Data for a Bullwhip impacted LVHV system in response to customer demand.

4.0 State Estimation and Resource Availability of Supply Chain Control System

Improving supply chain performance is highly dependent on coordination and information sharing between all agents in the supply chain network. Enabling the visibility of information benefits all participating agents by reducing the uncertainty on production and resource availability, whose processes depend on upstream or downstream supplier activities [44]. However, there are a number of barriers that are preventing the commitment of information sharing among the supply chain agents such as threats of information security, technological disparities, and financial constraints [71, 13, 76]. Because of this, the information available to supply chain agents is limited and may only consist of suppliers that they have contractual relationships with or agents who are immediately upstream or downstream in their supply chain.

To overcome this, the internal states of the supply chain are estimated using state estimation techniques. State estimation is a method of determining the current state of a complex system that contains noisy measurements or inferred states [3]. When successfully applied to process monitoring, state estimators can provide an estimate of an unmeasured state that is essential to provide information about any plant such as space craft, autonomous vehicles, or robotic manipulators [41, 66, 67]. For the supply chain case, state estimation techniques are applied to the scenarios developed in Chapter 3. This provides a means of inferring states, such as inventory levels of suppliers, from measurements of immediate upstream suppliers.

In this research, state estimation is achieved by using the probabilistic perspective of Bayesian processing. Bayesian signal processing is applied to the supply chain models to estimate the inventory positions of upstream suppliers inventory positions. This estimation can be achieved using several different Bayesian processes, such as the Kalman filter or particle filter, to provide a means of inferring the inventory level of suppliers from measurements of immediate upstream suppliers. By successfully estimating the states of upstream resources, uncertainty surrounding resource availability is reduced.

4.1 Bayesian Signal Processing and State-Space Models for Bayesian Processing

Bayesian signal processing is used to estimate the probability distribution of a random signal in order to employ statistical inferences and provide a better signal estimation [11]. These statistical inferences extract the desired signal from noisy uncertain measurement data. The Bayesian approach begins with the estimate of the underlying conditional probability distribution, $P(X|Y)$, then the inferences to extract the estimated signal, $\hat{X}$, are performed such that:

$$\hat{P}(X|Y) \Rightarrow \hat{X} = \text{argmax}_X \hat{P}(X|Y) \tag{4.1}$$

where the associated conditional probability, $P(X|Y)$, is defined as the posterior distribution because the estimated signal is conditioned after the measurements have been obtained. Since the posterior distribution is used, the estimation method is deemed Bayesian due to the use of Bayes' rule:

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)} \tag{4.2}$$

where $P(X)$ is defined as the prior distribution, $P(Y|X)$ is defined as the likelihood, and $P(Y)$ is defined as the evidence. As more data is obtained or measured, the prior evolves into the posterior distribution with a peak that narrows towards the true desired value.

Bayesian signal processing applies Bayes' rule to dynamic cases, which yields the following joint dynamic distribution:

$$P(X_t|Y_t) = \frac{P(Y_t|X_t)P(X_t)}{P(Y_t)} \tag{4.3}$$

where the added subscript for $X \rightarrow X_t$ and $Y \rightarrow Y_t$ define the dynamics as a function of time. This implies that the dynamic approach of Bayesian signal processing yields an identical estimation to non-dynamic cases:

$$\hat{P}(X_t|Y_t) \Rightarrow \hat{X}_t = \text{argmax}_{X_t} \hat{P}(X_t|Y_t) \tag{4.4}$$

Therefore, Bayesian signal processing enables the use of statistical inferences on desired estimates when the posterior distribution is determined.

In Chapter 2, a generic state-space representation was developed for a linear time-invariant continuous-time and discrete-time model. From a Bayesian approach, it is assumed that the state variables propagate through time according to some probabilistic mechanism with the addition of process and measurement noise. In discrete-time, the state-space representation becomes:

$$\begin{aligned} x[t] &= f(x[t-1], u[t-1], w[t-1]) \\ y[t] &= h(x[t], u[t], v[t]) \end{aligned} \tag{4.5}$$

where w and v are the process and measurement noise sources, respectively, and u as a known input to the system. The model begins with the state vector containing an initial distribution, $P(x(0))$, that propagates throughout the model according to the probabilistic transition distribution, $P(x(t)|(x(t-1))$.

The model implies that the measurements evolve from the conditioned likelihood distribution on the state variables, $P(y(t)|x(t))$. The model also takes on the Markov property. The Markov property defines that all future states of the process depend only upon the present state, then the state at time t is obtained by the previous state $x(t-1)$ as well as information about the underlying conditional probability. When the state reaches time t, then the likelihood probability and the new measurement, $y(t)$, is updated or corrected. Since the state propagates in a probabilistic manner with process and measurement noise, the application of Bayesian estimation on the state-space model extracts an unobserved or hidden state variable.

4.2 Linear Inventory Position Model with Kalman Filter

State estimation techniques are used to determine whether suppliers upstream have resources available. The sought after state is inventory position. The estimated state of upstream supplier inventory position has the potential. Estimation is achieved through the use of a Kalman filter to provide a means of inferring the inventory level of suppliers from measurements of immediate upstream suppliers.

The Kalman filter is applied to the state-space model discussed in Section 3.2. For this research, the parameters that defined the inventory setpoint position and inventory-replenishment policy remain unchanged for both healthy and bullwhip impacted models. The state-space model is assumed to be linear, time-varying with additive Gaussian noise to the process and measurement equations to account for the uncertainty in random fluctuations of inventory position.

Given that the dynamics of the supply chain upstream are clouded with uncertainty, the Kalman filter allows the estimation of the inventory position state through its two stages of prediction and innovation (update). The algorithm begins by defining an initial state vector, $\hat{x}(0|0)$, and an initial covariance matrix $\tilde{P}(0|0)$. Thereafter, the process begins the prediction step, also referred to as the time update step, where a projection of the estimated state and error covariance is computed given information about the previous time step. Since this is the first projection, the initial estimates are used to compute the prior estimate, $\hat{x}_{k|k-1}$, and the prior error covariance, $\tilde{P}_{k|k-1}$.

With a prediction of the state and error covariance, the measurement update or correction step is performed. In this step, the estimate of the state, $\hat{x}_{k|k}$, is computed by using the Kalman gain K_k and the observed output at the current time step, y_k. The error covariance, $\tilde{P}_{k|k}$, is updated to be used for future estimates in the next time step. The values computed in this step are propagated to the inputs for the $k+1$ step, thus leading back to the prediction step and the start of the iterative algorithm. The algorithm for implementing a Kalman filter is shown in Algorithm 1. The full derivation of the Kalman filter can be found in [11].

Figure 4.1 shows the Kalman filter results for estimating the inventory position of the suppliers. Overall, the Kalman filter successfully estimates upstream supplier inventory assuming a linear model with error converging to zero within a few time steps. By successfully estimating upstream supplier inventory, the uncertainty is reduced with regards to resource availability. To this end, the Kalman filter provides estimates of resource availability and can be used to in the decision making process of supply chain management to satisfy the goals of their company.

For the bullwhip impacted model, the Kalman filter remains consistent with its estimation of the inventory position as it parallels the true state. The estimation of the inventory positions has an error that does not diverge despite estimation of an unstable model. The error appears to decline after settling at 1.5 units and 2 units for supply chain agent 1 and supply chain agent 2, respectively. The Kalman filter results and their errors are shown in Figure 4.2.

Input: Initialize: $\hat{x}(0|0)$, $\tilde{P}(0|0)$

for $k = 0$ **to** N **do**

  begin Prediction:

    $\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_{k-1}$

    $\tilde{P}_{k|k-1} = A\tilde{P}_{k-1|k-1}A' + Q$

  end

  begin Measure:

    Read y_k

    $e_k = y_k - C\hat{x}_{k|k-1}$

  end

  begin Calculate Gains:

    $\Sigma_k = C\tilde{P}_{k|k-1}C' + R$

    $K_k = \tilde{P}_{k|k-1}C'\Sigma_k^{-1}$

  end

  begin Update:

    $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k e_k$

    $\tilde{P}_{k|k} = [I - K_k C]\tilde{P}_{k|k-1}$

  end

  begin Delay:

    $\hat{x}_{k|k} \rightarrow \hat{x}_{k-1|k-1}$

    $\tilde{P}_{k|k} \rightarrow \tilde{P}_{k-1|k-1}$

  end

end

begin Return data:

  $\hat{x}_{k|k}$, $\tilde{P}_{k|k}$, $\quad i = 0 : N$

end

Algorithm 1: Kalman filter algorithm.

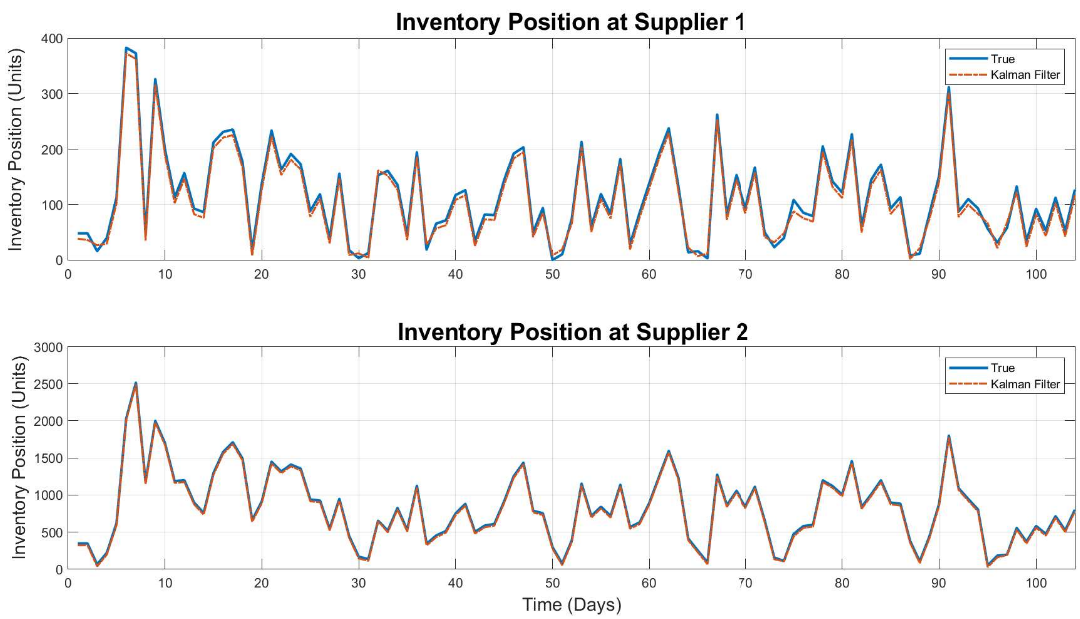


Figure 4.1: Kalman filter results on healthy configuration of the supply chain for estimation of upstream supplier inventory position.

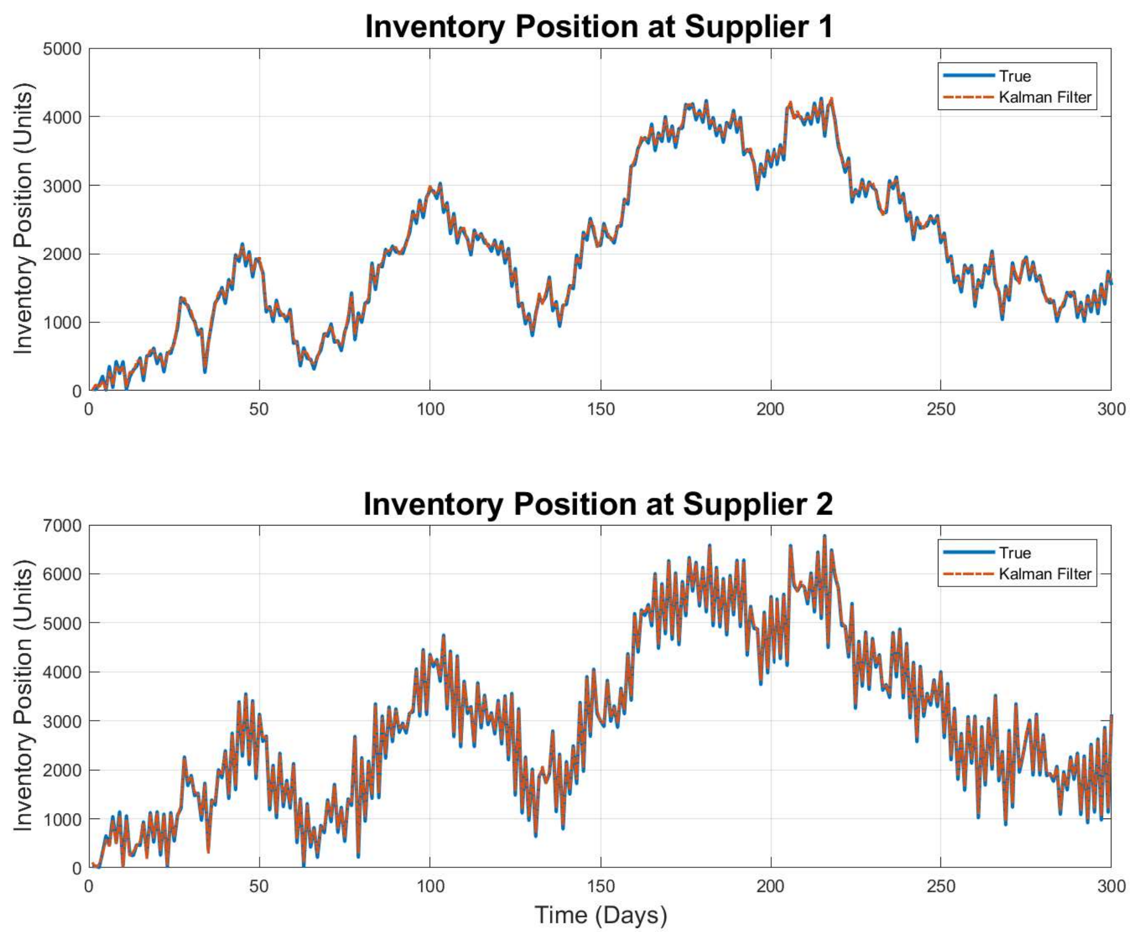


Figure 4.2: Kalman filter results on a bullwhip configuration of the supply chain for estimation of upstream supplier inventory position.

4.3 Non-linear Capacity Constraint Back-Order Model with Particle Filter

In Section 3.3.3, a nonlinear model due to capacity constraints was developed to generate order-book and backlog data for a low-volume, high-value (LVHV) supply chain with the addition of process and measurement noise. The Kalman filter designed for the linear model is not be able to estimate the states of the model because the Kalman filter is limited to linear models [17]. To overcome this, a particle filter is developed to estimate the states associated with the inventory process.

Particle filtering is a Monte Carlo method that uses sequential estimation of relevant probability distributions using discrete random approximation methods and importance sampling techniques. The particle filter begins by generating a set of particles from an *a priori* distribution about the initial state and using the initial state to observe the initial measurement. As the model steps through time, the set of particles are propagated through the state-transition model to produce a new set of state particles. The new set of state particles are used to update the observation, thereby producing a set of particles surrounding the next observed measurement. Weights are generated for each measurement particle defined by the probability of the measurement particle given the true measurement at that time step.

The weights are normalized to form a the posterior probability distribution. From this new distribution, random samples are drawn to generate new particle estimates. When sampling randomly over this distribution, values are selected based upon their statistical significance. Those that are statistically significant are the higher valued weights, which are more likely to be chosen. This step ensures that the newly sampled weights are more likely to be near the actual value, which becomes the new set of particles. Finally, the final estimate is determined by averaging the set of particles. The particle filter algorithm applied to state-space models is described in Algorithm 2. The histogram and probability distribution for several states are shown in Figure 4.3 and Figure 4.4, respectively.

The particle filter successfully estimates the following states of the nonlinear MTS/MTO model: input demand of the MTO system, the completion rate of the MTO system, the actual inventory of the MTS system, and the back orders of the MTS system. This estimation provides valuable information about the health of the supply chain and the ability to estimate upstream processes reduces uncertainty in resource availability. The results are illustrated in Figure 4.5.

Most importantly, the particle filter successfully estimates the states of upstream suppliers when

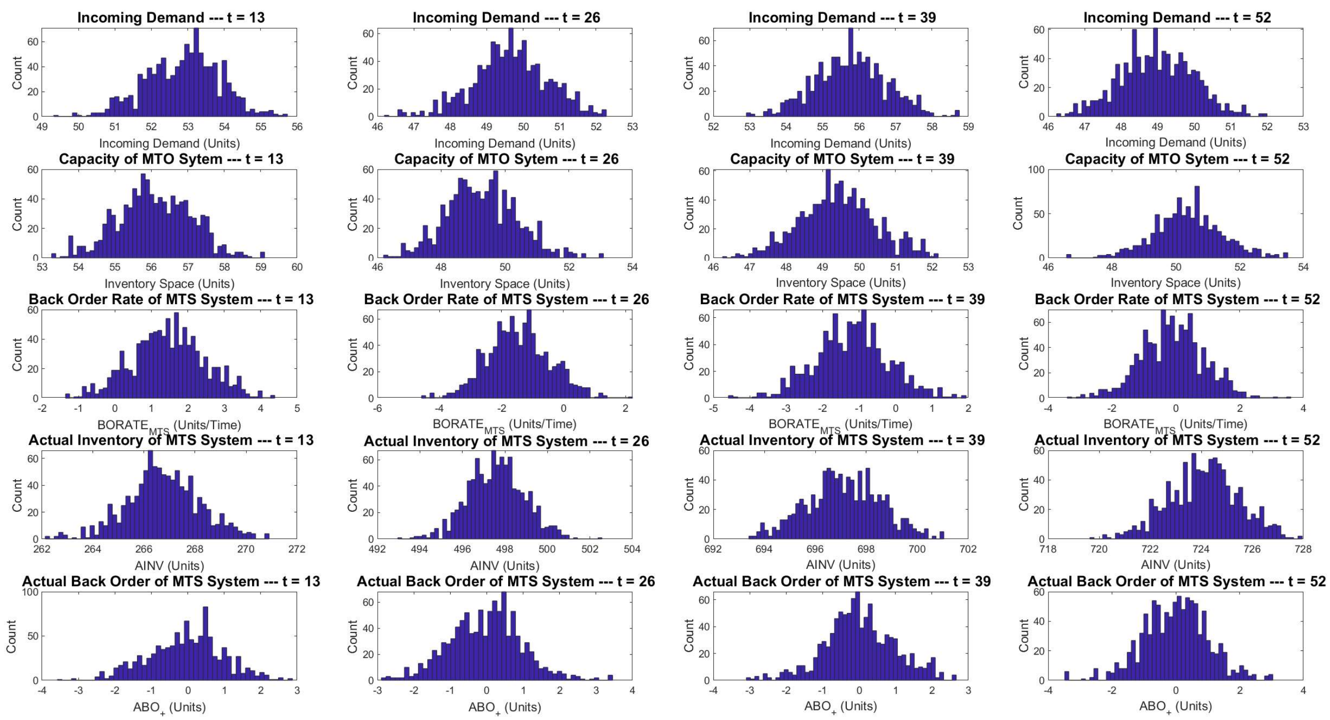


Figure 4.3: Histogram of states generated by propagating particles through the system for several time steps of the MTO/MTS hybrid model.

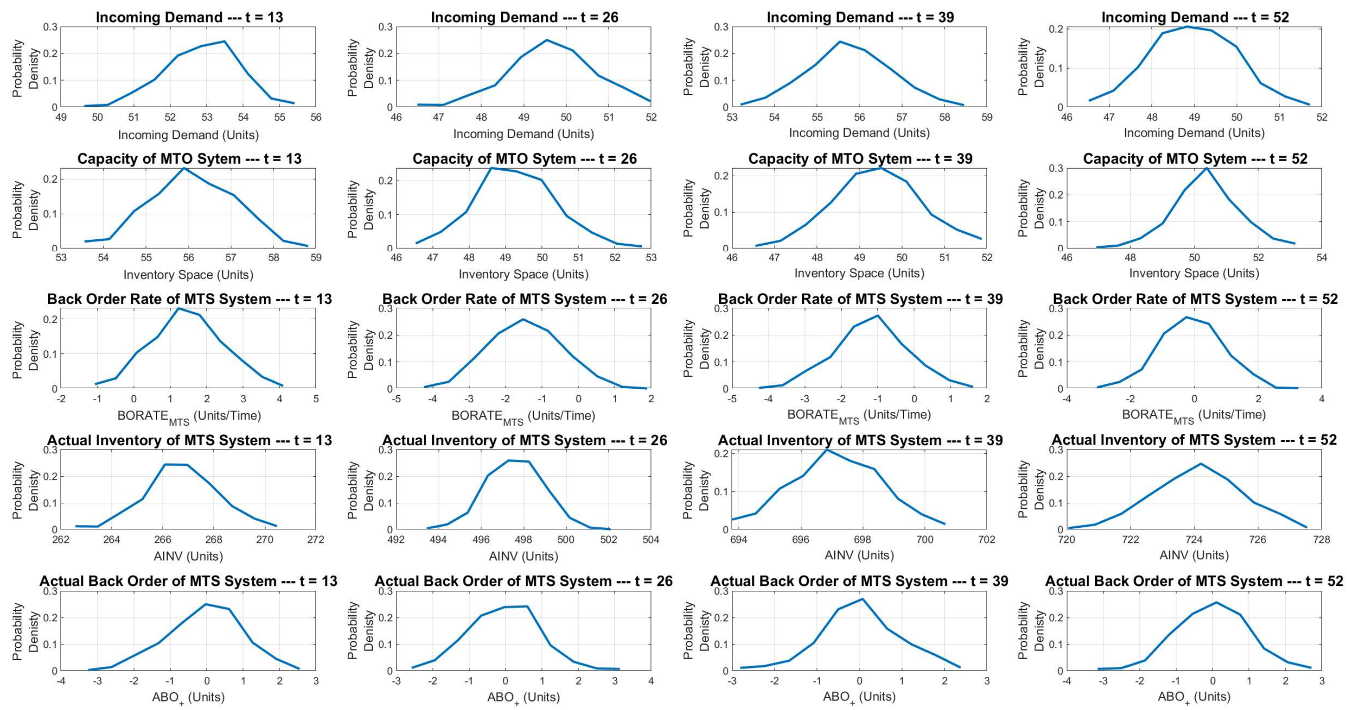


Figure 4.4: Probability densities of states generated by propagating particles through the system for several time steps of the MTO/MTS hybrid model.

Input: Initialize $x_i(0) \rightarrow P(x(0)); W_i(0) = \frac{1}{N_p}; i = N_p$

for $t = 0$ **to** T **do**

  for $i = 0$ **to** N_p **do**

    begin Propagate particles through process

      $x_i(t) \leftarrow A(x(t-1), u(t-1), w_i(t-1))$

      $w_i \; P(w_i(t))$

    end

    begin Update weights

      $W_i \leftarrow C(x(t), u(t), v(t))$

    end

  end

  begin Normalize weights

    $\mathcal{W}_i(t) = \frac{W_i(t)}{\sum_{i=0}^{N_p} W_i(t)}$

  end

  for $i = 0$ **to** N_P **do**

    begin Resample with decision

      $\hat{N}_{\text{eff}} = \frac{W_i}{\sum_{i=0}^{N_p} W_i^2(t)}$

      if $\hat{N}_{\text{eff}} \leq N_{\text{thres}}$ **then**

        Accept

      end

      else

        Resample

      end

    end

  end

  $x_i(t) \leftarrow W_i^{\text{new}}(t)$

  begin Estimation through expected value

    $\hat{x}(t) = \mathrm{E}\{x_i(t)\}$

  end

end

Algorithm 2: Particle filter algorithm with resampling.

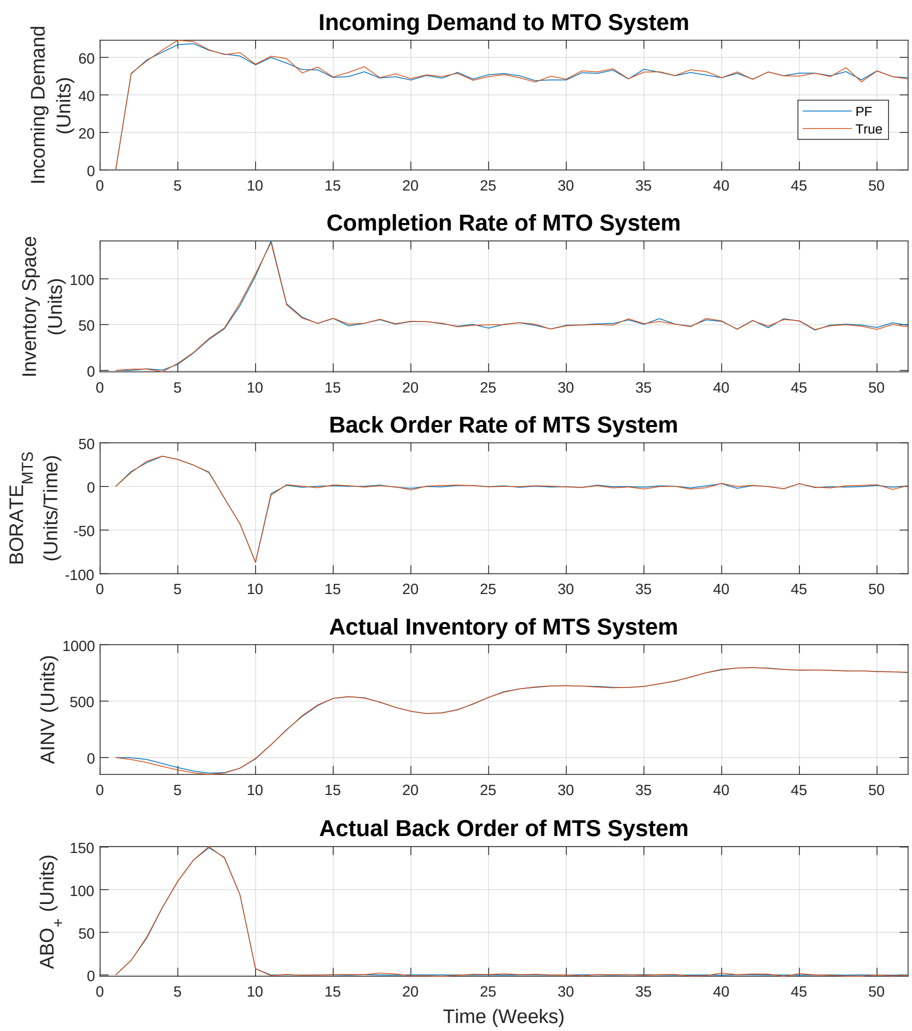


Figure 4.5: Estimated states from the particle filter applied to the healthy configuration of the MTO/MTS hybrid model.

the system is unstable e.g. when a bullwhip occurs leading to an accumulation of back orders. This estimation provides valuable information about the health of the supply chain and the ability to estimate upstream processes reduces uncertainty in resource availability. The estimated results of the particle filter applied to the bullwhip impact MTO/MTS model is illustrated in Figure 4.6.

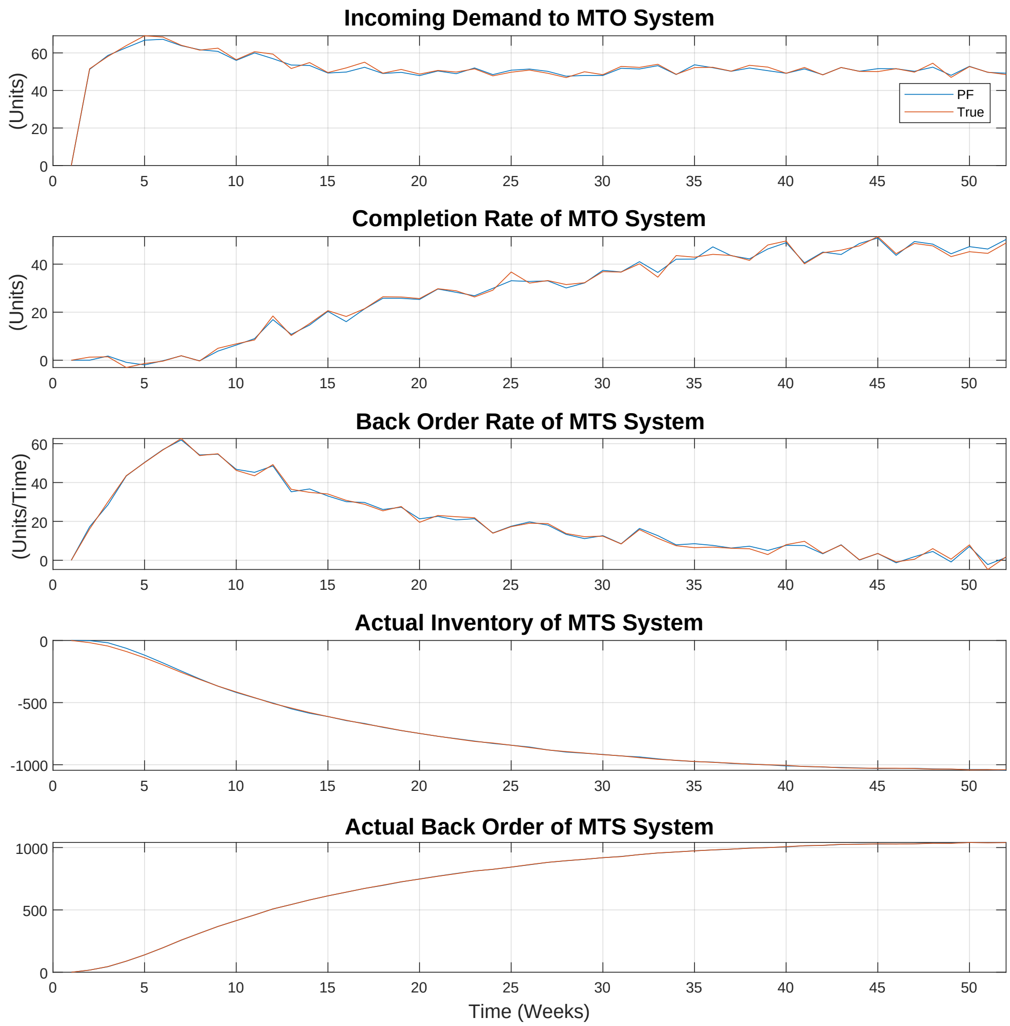


Figure 4.6: Estimated states from the particle filter applied to the healthy configuration of the MTO/MTS hybrid model.

5.0 Supply Chain Uncertainties and Bayesian Networks

The supply chain consists of a number of uncertainties that have the ability to negatively impact the flow of resources and information at all supporting areas such as location, inventory, transportation, and production. The uncertainties within the supply chain are affected by events and can encompass a vast range of incidents along with their associated impact on the supply chain. In terms of supply chain management, these uncertainties can cloud the decision making process when selecting the appropriate supplier that can meet their company's goals.

This process is known as the supplier selection, where supply chain management attempts to identify, evaluate, and contract with suppliers. The main objective of supplier selection process is to reduce risk and to increase the overall value to the purchaser, and develop closeness and long-term relationships between buyers and suppliers. To address the uncertainties and how risks impact the flow of goods and resources in supply chain networks, a Bayesian network is constructed to model events surrounding the supply chain and ultimately the supplier selection decision process.

In this section, Bayesian networks are introduced along with their advantages when applied to analyzing supply chains. Bayesian networks are then constructed around the two scenarios discussed in Chapter 2, which includes a Bayesian network for a ship-to-stock (STS) supply chain, and a Bayesian network for the low-volume, high-value (LVHV) supply chain. Both Bayesian networks include the uncertainties of the supply chain, including the synthetic inventory-production data generated in Chapter 2. The synthetic data is integrated in the Bayesian network to determine the likelihood of available resources. Finally, several suppliers are considered in each Bayesian network to provide a data-driven decision making approach to the supplier selection process.

5.1 Data-driven Decision Making for Supply Chain Management — A Bayesian Network Approach

The ability to monitor, plan, and control the uncertainties in the supply chain is an arduous task due to the vast number of risk events that can lead to disruptions. Support for decision makers in the face of uncertainty can be achieved through Bayesian networks. Bayesian networks enable a preventive assessment of risks rather than a reactive choice to their consequences. The advantages of Bayesian networks provide an inference on the cause and effect nature that models how events between the interdependent agents in the supply chain propagate throughout the entire network. In this case, inference is defined to take on the Bayesian perspective by updating the probability for a hypothesis as more evidence or information becomes available. To this end, Bayesian networks can be used to monitor events, update their probability of occurrence given new information, and plan mitigation decisions as a preventative measure to control or reduce the consequences.

Bayesian networks can be applied to the risks imposed on the supply chain due to their uncertainty and causal relations between risks and their consequences on a company's finances, the overall lead-time, and resource availability. Before the use of Bayesian networks, probabilistic inference was computed with the conditional probabilities of events from known sources using Bayes theorem:

Theorem 1 (Bayes Rule)**.** *Consider two events A and B such that $P(A) \neq 0$ and $P(B) \neq 0$:*

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{5.1}$$

Using Bayes rule, the conditional probabilities of an event are computed given the known information.

Application of Bayes theorem leads to a representational device that organizes the knowledge about a particular set of circumstances into a coherent whole known as Bayesian networks. To this end, Bayesian networks can be employed as a graphical modeling tool for specifying probability distributions that can address uncertainty in the domain of knowledge in question. Bayesian networks are directed acyclic graphs (DAG) that consist of nodes and arcs as shown by the simple network in Figure 5.1. The nodes depict variables of interest and the arcs depict casual relationships between the variables of interest. The Bayesian network encodes the causal relationships as conditional probabilities between variables. By explicitly identifying which variables influence others, cause and effect can be modeled. For example, the child Node C is influenced by its parent nodes, Node A and Node B. [16].

By applying Bayes rule, the conditional relationships between the nodes in Figure 5.1 generates the following joint distribution:

$$\mathrm{P}(A, B, C) = \mathrm{P}(C|A, B)\mathrm{P}(A)\mathrm{P}(D) \tag{5.2}$$

Two Bayesian networks are constructed to fit the scenarios formulated in Chapter 2: (1) a Bayesian network for a ship-to-stock (STS) supply and (2) a Bayesian network for a low-volume,

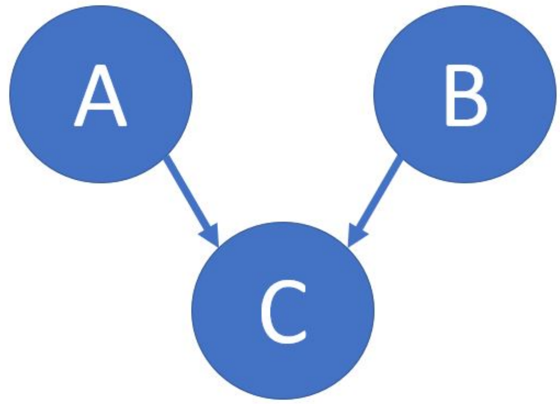


Figure 5.1: Simple Bayesian network.

high-value supply chain. Both networks aim to provide a data-driven decision making process for supply chain management.

The construction of a Bayesian network involves three steps:

1. Decide on the set of relevant variables and their possible values.
2. Build the network structure by connecting the variables into a DAG.
3. Define the conditional probability tables (CPT) for each network variable.

The first step involves defining a set of relevant variables and their possible values surrounding the supply chain for each scenario. In this research, the set of variables and their values are defined through an ontological approach, which simultaneously defines the structure of the supply chain networks. This includes the dependencies between supply chain agents, the risk events that impede the flow of goods and information, the desired set of goals set by the supply chain management, and the opportunities to provide a positive impact on the supply chain.

The second step consists of building the network structure into a DAG. The supply chain networks created in the previous step already contain the relationships between supply chain agents. Therefore, the DAG is easily generated by using the knowledge of the supply chain networks. Additional network arcs are added to account for the risk events imposed on the supply chain networks.

The final step defines the CPT tables for each network variable. The CPTs consider the conditional dependence of risk events occurring and how they impact the likelihood of on-time delivery. To this end, the generated CPTs in the final Bayesian networks aid supply chain management in their decision making in terms of the supply selection process by evaluating if the suppliers have a higher probability of on-time delivery.

5.1.1 Ontological Approach to Supply Chain Network Development with Risks

Elicitation of expert knowledge to develop a supply chain network was attempted, however, the sought after supply chain data contained sensitive information that many experts refused to share. To overcome this, an ontological approach is used to develop the supply chain network, the events, and their likelihood of occurrence. An ontology is a set of concepts and categories in a subject field that contains their characteristics and the relationships between them. Supply chain ontologies have been developing for several years in order to solidify a standardization of the supply chain domain. When performed successfully, the ontology provides meaningful exchanges between experts and/or data systems in the field because of the common information [96].

The ontology was built through an extensive literature review and a number of personal interviews with experts and decision makers in the supply chain. From the ontology, the three steps for Bayesian network development can be accomplished and then the Bayesian networks are formulated for the two scenarios.

The set of relevant variables in the supply chain are the supply chain agents, risk events and their propagating effects on the goals of the company, and the opportunities to mitigate the risk events. Table 5.1 lists a generalized set of variables with their associated values.

Most supply chains contain a vast number of acting agents to provide goods and services to its market. The set of variables must contain the all participating agents in the supply chain. Additionally, supply chain agents defined in the set of variables contain values of unreliability. This value defines an agent's inability to meet the goals of the customer for a specified period of time [38]. For this research, unreliability is defined as the probability that the agent will fail to deliver the product. Conversely, reliability is defined as the probability that the agent will successfully deliver the produce on-time.

The set of variables in the Bayesian network also includes events. Broadly, events are those that have a negative impact on an investment. In terms of the supply chain, risks focus on the

Table 5.1: General list of the set of variables and their values that are used to construct a Bayesian network.

Set of Variables	Values
Supply Chain Agents	P(Unreliability)
Risk Events	P(Risk Occurring) + Negative Impact
Goals	Evidence Based
Mitigation Options	Evidence Based + Positive Impact

probability of events that result in a loss or the impedance on the flow of information, materials, or products from original suppliers to the end-user [73, 30].

From an ontological perspective, the supply chain approach to events are categorized as a purely event-oriented concept and have likelihood of occurring as their associated values. Certain events impact supply chain agents differently meaning there are controllable and uncontrollable factors. For example, a controllable supplier risk is a quality issue. The reason it is controllable is because the end customer has the ability to send a representative to the supplier to ensure the quality of the product. On the other hand, an uncontrollable supplier example would include a natural disaster.

The set of variables must also account for the propagating consequences of risk events on the goals set by supply chain management. Events are often only considered as isolating events, with little consideration on their ripple effect. This ripple effect of a risk event can impact the lead-time and delay the end product from reaching the customer, which then propagates to the finances of the company. In this case, the risk event evolves to a disrupting event, characterized through likelihood of occurrence and severity, and a consequential circumstance that threatens the normal course of business operations.

This deviation of the objectives set by supply chain management requires further classification of risk events with an additional financial parameter such that if an event occurs, the expected total cost of the product is subject to change. To this end, the set of variables in the Bayesian network must also consider the goals of the company and their financial impact when events disrupt the flow of information, materials, or products.

A brief example includes if a transportation event occurs, consequentially delaying the product from reaching the end customer. Since the delayed occurred, there may be financial repercussions that reflect the product not being delivered on-time. The goals set by that supply chain management with their associated risk factors and penalties must be accounted for in the set of variables, which can be found in Table 5.2.

Finally, the set of variables must include the opportunities to improve the supply chain. This comes in the form of mitigation techniques and contingency strategies to reduce the likelihood of an event occurring. This is achieved by introducing qualitative Boolean evidence to the set of variables. The qualitative decision may reduce events by securing evidence to a mitigation node that propagates the statistical inference of successfully mitigating a risk throughout the model in an attempt to secure the financial goals of the company.

However, mitigation decisions come at a cost to the company. Planning and mitigating events by selecting decisions requires additional financial resources from the company, whether its a selection decision of a supplier visit or a back-up-plan decision to ensure transportation of the product is on time. The addition of the mitigation decision nodes enables decision makers the ability to plan and potentially reduce the likelihood of events with the trade-off of additional costs. In this research, each mitigation strategy is deployed to the likelihood of the events and ultimately the risks propagating impact on lead-time.

For example, if a supply is having quality issues at their plant, the customer may have the option to send an employee to oversee the operations to ensure the quality meets their company's standards. At the same time, if the customer chooses to send an employee, then the the company has to pay for their expertise at the supplier. By doing so, this may reduce the likelihood of the quality event occurring. The mitigation techniques paired with their positive impacts can be found in Table 5.3.

5.1.2 Directed Acyclical Graph Generation from Supply Chain Network

The second step in the Bayesian network development requires a definition of conditional interdependence among the set of variables in the supply chain. The structure and dependencies between supply chain agents in Figure 5.2 resembles the structure and dependencies of a directed acyclical graph (DAG). In other words, the supply chain network replicates the dependencies between agents and how the flow of information, materials, or products moves among the facilities. Therefore, the DAG can easily be translated by understanding the flow of goods and materials from Figure 5.2.

By including the set of variables along with their conditional dependencies represented through an arc, a DAG is constructed. This requires extending arcs between parent nodes and child nodes. Parent nodes define the original states and are the inputs to the network. They have arcs extending from their bodies and pointing towards its children. The child nodes show a conditional probability towards its parents as indicated by the arc.

As an example, consider that a supplier is required to meet a lead-time goal set by its customer. However, this supplier has a quality event associated where the customer has the mitigation option to send an employee to oversee the operations. From the DAG perspective, the lead-time goal is dependent on the supplier's reliability, the supplier reliability is dependent on the quality event, and the quality event is dependent on the evidence-based mitigation option. Additionally, the mitigation expense is dependent the mitigation option and the penalty is dependent on the event. Figure 5.3 illustrates this DAG example.

5.1.3 Conditional Probability Tables for Bayesian Network Construction

The conditional probability tables (CPT) are determined from the creation of the DAG. Given the probabilities initialized by the parent nodes and conditional probabilities associated with the children nodes, the probability of a given series of events can be calculated as follows:

$$P(X_1 = x_1, X_2 = x_2, ..., X_n = x_n) = \Pi_{i=1}^{n} P(X_i = x_i | Parents(X_i)) \tag{5.3}$$

where $P(X_i = x_i | Parents(X_i))$ is the probability that the node for random variable X_i is in state x_i given the states of the parent nodes of X_i.

When empirical data is unavailable to populate the CPTs, experts may specify the conditional probabilities [69]. Through expert knowledge obtained from the supply chain ontologies, the CPTs are generated to depict probabilistic relationships between the set of variables in the Bayesian network. However, for most instances there is insufficient quantitative or reliable data for populating the CPTs. Under these circumstances, methods can be applied during the ontological review to translate qualitative descriptions written by experts to probabilities using the scale in Figure 5.4. Thereafter, the translated probabilities can be used to estimate the CPTs in the Bayesian network supply chain environment

5.1.4 Update Beliefs and Reasoning with Bayesian Networks

Bayesian updating is the computation of the posterior probability distribution for a set of nodes, given observations for some evidence nodes. In the Bayesian network the value that is observed is conditioned on some observation. The process of Bayesian inference is performed via a flow of information through the network [43].

Reasoning with a Bayesian network is done by updating the probabilities, which involves using new information or evidence to compute the posterior probability distributions. The constructed networks are used for forward reasoning and reverse reasoning of risk. Forward reasoning is to modify the value of the corresponding risk nodes in BN according to the received risk-related information, and then observe the changes of each node and analyze the influence of the changing node on other risk items. Reverse reasoning is to infer the key influencing factors by adjusting the assignment of a certain risk item and observing the changes of relevant nodes.

Table 5.2: List of goals that supply chain management attempts to satisfy.

Goals	Description	Risk Factors	Impact
Efficiency	Reduce wasted materials, expenses, work hours, delivery time.	Controllable and Uncontrollable Risk Factors	Increases expenses, delivery delays, reduces profit.
Resilience/ Stability	Capable of providing an efficient response to return to the original state of the supply chain after a disruptive event.	Uncontrollable Risk Factors	Delivery delays, decrease in customer satisfaction, reduced production and profit.
Supplier Reliability	Ability to select from a supplier portfolio to ensure goods are delivered on-time.	Controllable and Uncontrollable Risk Factors	Decreases supplier portfolio, increase expenses
Risk Mitigation	Planned and systematic strategies to reduce the likelihood and impact of risks.	Controllable Risk Factors	Increases likelihood of risk events, wasted expense on mitigation strategy.

Table 5.3: List of mitigation options that supply chain management can employ to positively impact the supply chain.

Mitigation Options	Impact
Supplier Visit	Reduces poor quality of ordered products.
Diversify Suppliers	Ensures on-time delivery and low costs.
Insurance	Reduces financial losses due to in-transit risks but increases lead-time.
Technology Upgrade	Increases planning, scheduling and internal processes, reduces forecasting errors.
Culture Training	Strengthens business relations and customer satisfaction.
Buffer Stock	Ensures available resources.
Contingency Transportation	Reduces downtime of transportation and impact on lead-time

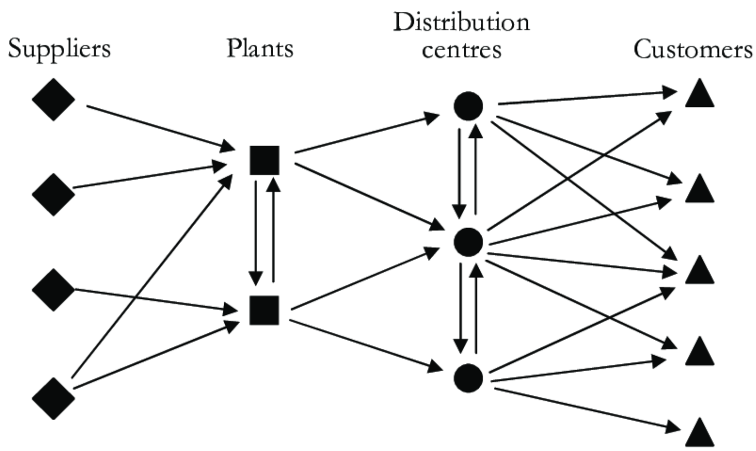


Figure 5.2: A general supply chain network.

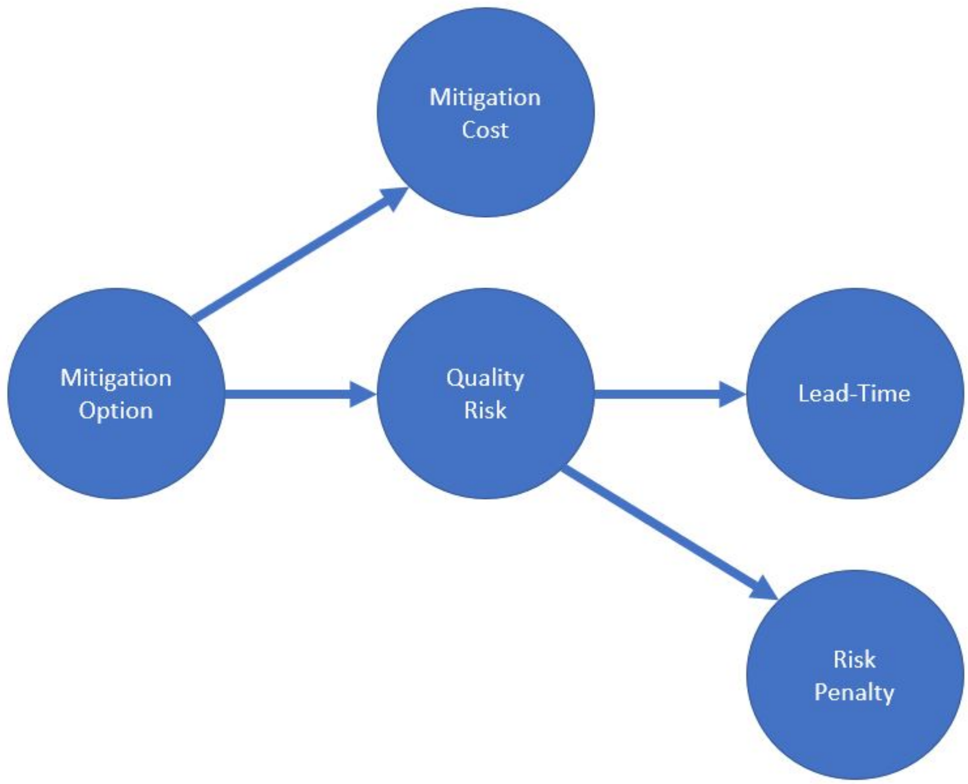


Figure 5.3: An example of a supply chain goals, risks, and mitigation strategies as a directed acyclical graph.

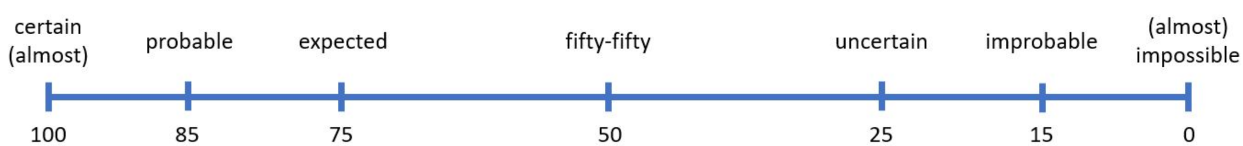


Figure 5.4: Probabilistic elicitation scale.

5.2 Bayesian Network Construction for Ship-to-Stock Supply Chains

The steps in Section 5.1 define the basic building blocks for constructing a general Bayesian network for a supply chain. This research will take advantage of the definitions to construct a Bayesian network depicting a ship-to-stock (STS) supply chain with an integrated resource availability model from the synthetic data generated in Section 4.

The Bayesian network aims to help supply chain management with the supplier selection process. The decision maker has an illustrative perspective of the company's supply chain including two immediate upstream supplier nodes, where each supplier has their own upstream suppliers to account for inventory-production activity risks. Additionally, the Bayesian network contains event nodes impacting the immediate upstream supplier nodes, financial goal nodes set by supply chain management, and mitigation option nodes. The Bayesian network is developed using GeNIe Modeler [8]. Figure 5.5 depicts a high-level Bayesian network containing the dependencies between parent and child nodes.

For this research, the Bayesian network for the supplier selection process in Figure 5.5 is assumed to have two competing suppliers. Further, it is assumed that supply chain management is attempting to satisfy one supplier performance metric in their supplier selection process. In this research, that supplier performance metric is to ensure that the ordered component is delivered on-time given the set lead-time. Additionally, it is assumed that the immediate upstream suppliers, Supplier 1 and Supplier 2, have a historic relationship with the end-customer. This implies that the associated risks have the option to be mitigated through techniques and contingency plans enabled by supply chain management. Finally, this research assumes that Supplier 1 has a lower overall risk when compared to Supplier 2 to highlight the strengths of Bayesian networks as a decision making tool.

5.2.1 Bayesian Network Learning from Synthetic Inventory Data

In Section 4.2, state-estimators were developed to estimate the inventory positions of the synthetic inventory data from a three-tier series supply chain model. The data produced from the model is used as a training set for Bayesian network learning to be performed. Bayesian network learning uses the training data to provide probabilistic inference on hypotheses by populating the CPTs of a resource availability model within the Bayesian network. This process is outlined in

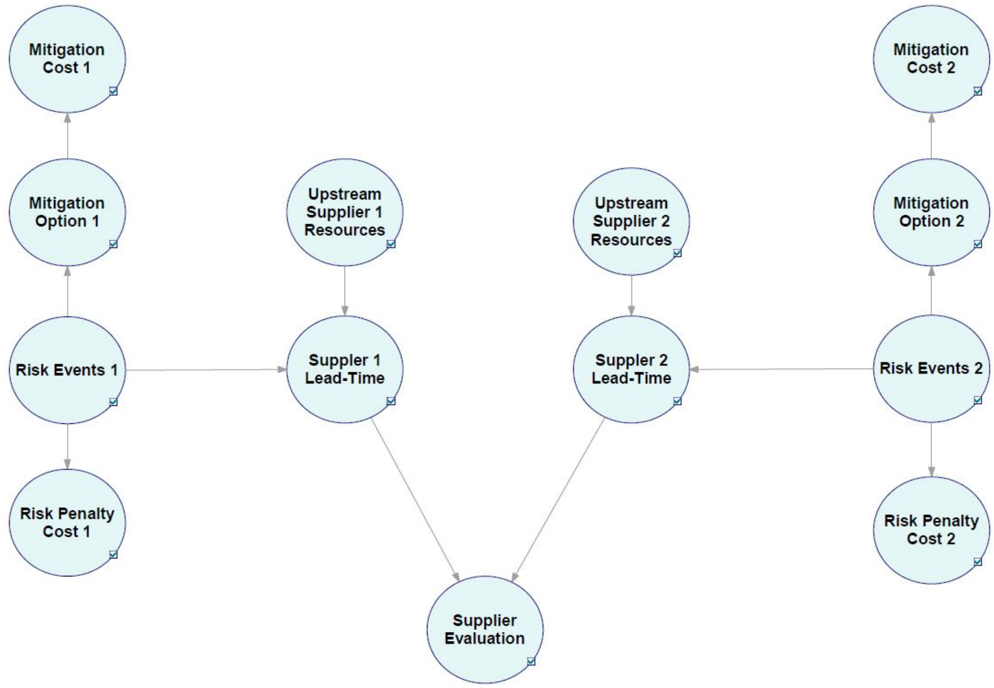


Figure 5.5: High level depiction of the ship-to-stock Bayesian network.

Figure 5.6.

GeNIe has the capability of generating the CPTs for a model given there is suitable data for learning. Bayesian network learning is a probabilistic approach to building models, which combines prior knowledge with learning from data. In order to do so, a Bayesian network depicting the three-tier supply chain is constructed. The constructed Bayesian network shows how the input demand along with the flow of goods between suppliers has a conditional relationship between the inventory positions. This Bayesian network is shown in Figure 5.7. The goal of this network is to determine if resources are available throughout the entire supply chain given the inventory-production data of the two upstream suppliers.

Two Bayesian networks were created from the two sets of synthetic data: (1) a network that provides the likelihood of available resources given a set of data whose model was not impacted by the step in input demand and (2) a network that provides the likelihood of available resources given a set of data that was impacted negatively by the step input demand simulating the bullwhip effect. The synthetic data is discretized into states using GeNIe. For this research, the final child node for resource availability contains two states as a measure of inventory health.

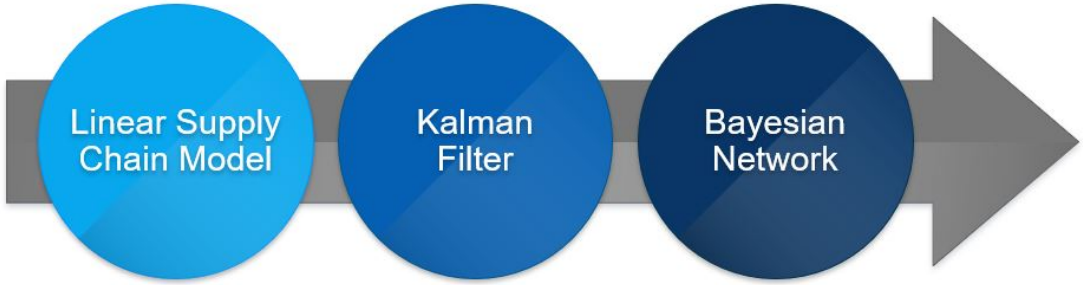


Figure 5.6: Process of integrating the synthetic data, Kalman filter, and Bayesian network model.

That is, if the node indicates HealthyResources then the likelihood of having a bullwhip impacted event is unlikely, thus resulting in inventory positions that can satisfy the end-customer's demand. The remaining discretized states for each node is shown in Figure 5.7 along with both models for each set of data.

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 [43]. GeNIe has the ability to automatically update beliefs in the network to provide a probabilistic inference to aid decision makers when considering their goals. Figure 5.8 shows the updated GeNIe results for the resource availability Bayesian network.

The updated networks provide a probabilistic inference on whether the supply chain has HealthyResource or UnhealthyResources. The network on the left illustrated in Figure 5.8 learned from the data set that contained typical behavior thus resulting in a 64% probability that the supply chain contains healthy resource levels. This learned Bayesian network inventory-production model is integrated into the final network where the Available Resources node acts as an arc extending to the Supplier 1 node as suggested in Figure 5.5. The network on the right illustrated in Figure 5.8 learned from the data set yields a probability of 87% for unhealthy resources, implying that this supply chain may have been impacted by the bullwhip effect.

This learned Bayesian network inventory-production model is integrated into the final network where the Available Resources node acts has an arc extending to the Supplier 2 node as suggested in Figure 5.5.

5.2.2 Building the Bayesian Network to Aid Supply Chain Managers in the Supplier Selection Process

There still exists a number of unaccounted for variables that were discussed in Section 5.1 that are needed in to generate the final Bayesian network. It has been established that the assumed goal set by supply chain management is to ensure on-time delivery. In the Bayesian network, this is reflected by including a Impacted Lead-Time node for each supplier and representing the lead-time as a normal distribution shown in Equation 5.4.

$$\text{Lead-Time} \sim \text{TNORM}(\mu = 16, \sigma^2 = 1, LB = 11, UB = 20) \tag{5.4}$$

where μ is the mean, σ is the standard deviation, LB is the lower bound, and UB is the upper bound. The TNORM is an extension of the normal distribution that is bounded to values that lie within a range and is readily available for implementation in GeNIe [10]. The TNORM is an appropriate distribution for lead-time since the mean value depicts the average amount of days for the end-customer to receive the ordered product within a bounded time frame. Figure 5.9 shows the Impacted Lead-Time as a TNORM node for Supplier 1.

The Impacted Lead-Time node is dependent on risk events, which negatively impact the lead-time by shifting the mean lead-time to the left, and mitigation options, which positively impact the lead-time by increasing the likelihood that the product is delivered on its averaged delivery time. The Bayesian network showing the supplier selection process, the risks each immediate upstream supplier, and their mitigation options for the STS supply chain is depicted in Figure A1, which can be found in Appendix A.

To reduce computational efforts, two risks are chosen: (1) Quality Risk and (2) Transportation Risk since these risk events are the most common to occur [37]. Both risks serve as umbrella terms for the individual events that can occur, for example, quality issues in products can range from safety recalls to inability to satisfy regulatory standards in production. Transportation risks range from poor quality in roads, proximity to ports, and weather conditions.

The risks in the Bayesian network can move into two possible states: RiskOccuring or NoRisk. The former defines the likelihood that the risk event will occur and the latter defines the likelihood that the risk event poses no risk at all.

All risk events are conditioned on mitigation options, in an attempt to plan and control the negative impact. This comes in the form of mitigation techniques in the Bayesian network by introducing qualitative evidence to the Bayesian network. The qualitative evidence is embedded in the decision nodes, OPTION - Transportation Mitigation and OPTION - Quality Mitigation, as a Boolean evidence-based observation for supply chain management to choose from. If supply chain management chooses to enable the mitigation option, then the decision maker must provide evidence to the mitigation node by selecting the Option Yes state.

The likelihood that items from a supplier are of sufficient quality or the items delivery is not suffering from a transportation delay, as measured by binary states, is conditioned on the selected evidence of the mitigation nodes. The conditional probability tables for the Quality Risk and Transportation Risk with their respective mitigation options is shown in Table 5.4.

From the table, the probability that a quality related risk event will occur for Supplier 1 with no option to mitigation is 8%. If the option to mitigate is chosen then the probability decreases to 5%. Similarly, for Supplier 2 the probability is 72% and if the mitigation option is chosen then the probability decreases to 42%. The table also includes the transportation related risk for Supplier 1 with no option to mitigate as a probability of 3% and an option to mitigate of 2%. Finally, for Supplier 2 the transportation risk with no mitigation option selected is 68%. If the mitigation option is chosen then the risk probability decreases to 54%.

However, any mitigation decision comes at a cost to the company. Planning and mitigating risk events by selecting desired states requires additional financial resources from the company, whether its a selection decision of a supplier visit or a back-up-plan decision to ensure transportation of the product is on-time. The trade-off of additional costs is constructed in the Bayesian network as Mitigation Cost nodes. These nodes are implemented as equation nodes to contain an if-statement that is conditioned on the option mitigation nodes. The GeNIe modeler has the capability of implementing Equation Nodes, which contains a user-input equation that describes an interaction with its parent node. The conditional equation for the Mitigation Cost equation nodes for each supplier are found in Table 5.5.

In the event that the risk event occurs, the risks propagate information to the Lead-Time Impact nodes that negatively impacts the overall lead-time as well as a Financial Penalty. For this research, the Lead-Time Penalty represents the number of days that the lead-time is impacted if a risk event has occurred and the Financial Penalty is the monetary value lost if a risk event were to delay the delivery of the product.

In the Bayesian network, the Lead-Time Penalty nodes affect the Impacted Lead-Time through an conditional statement. The same approach is used to account for the Financial Penalty nodes. The values for the Impacted Lead-Time are assumed to be more significant for Supplier 2 when compared to Supplier 1. This is reflected in Table 5.5 as conditional if-statements for each supplier in the network.

Both the Financial Penalty nodes and the Mitigation Cost nodes are tabulated to help aid supply chain management make financial trade-off decisions. The nodes are defined as equation nodes and contain simple summation expressions as shown below:

$$\text{TotalPenaltyCost} = \text{QualityPenalty} + \text{TransportationPenalty}$$

$$\text{TotalMitigationCost} = \text{QualityMitigationCost} + \text{TransportationMitigationCost}$$

For the supplier selection process, all risk event nodes for each supplier, along with their conditional relationships, are propagated to a Total Risk node, where the statistical inference for all potential risks are accumulated.

This is achieved by employing the multiplication rule for independent, probabilistic events. The general rule is shown below followed by an example used in the Bayesian network.

$$\text{P}(\text{A} \cap \text{B} \cap \text{C}) = \text{P}(\text{A})\text{P}(\text{B})\text{P}(\text{C})$$

$$P(\text{QualityRisk} \cap \text{TransportationRisk} \cap \text{Bullwhip}) = P(\text{QualityRisk})P(\text{TransportationRisk})$$
$$P(\text{Bullwhip})$$

This node has two states that consider the total amount of risk in the network: RiskOccurring and NoRisk. It should be noted that the Total Risk node is dependent on the Available Resources node that was discussed in Section 5.2.1 to propagate the risk of the upstream suppliers having available resources.

The information contained in the Total Risk node is then propagated to a Primary Criteria node for each supplier. It is necessary that the *Primary Criteria* node is conditional on the Impacted Lead-Time node and the risks for the respective suppliers as shown in Figure A1, which can be found in Appendix A. The Primary Criteria node considers all risks and impacted lead-times from both suppliers in the STS scenario by having its statistical inference take on two states: Late and On-Time. The purpose of these states is to provide supply chain management an assessment of each supplier, that is, the higher the probability for the state then the more likely the product will be delivered on-time.

5.2.3 Updating Beliefs and Reasoning with the Ship-to-Stock Supplier Selection Bayesian Network

Bayesian updating is the computation of the posterior probability distribution for a set of nodes, given observations for some evidence nodes. In the Bayesian network, the value that is observed is conditioned on some observation. Supply chain management has the ability to set evidence in through the mitigation options. The scenarios below show the impacts on the supplier selection process when certain mitigation options are selected.

Scenario 1: In this scenario, supply chain management has not selected any mitigation techniques for either supplier due to financial constraints. The updated Bayesian network presents the supplier criteria to supply chain management with a likelihood that Supplier 1 has a 71% chance of on-time delivery compared to a 36% chance of on-time delivery for Supplier 2. However, the probability for a total penalty cost of $10,000 is approximately 40%. The updated Bayesian network is shown in Figure A2, which can be found in Appendix A. The updated Primary Criteria nodes for Supplier 1 and Supplier 2 are illustrated in Figure 5.10a and Figure 5.10b, respectively.

Scenario 2: Supply chain management wants to increase the likelihood of on-time delivery for supplier 1 by sending an employee as quality control. The Bayesian network is provided with evidence in the OPTION - Quality Mitigation 1 node by enabling the Option Yes state. When updating the evidence for the whole network, the risk of quality related event decreases to 2% with the addition of a mitigation cost of $5000 . Additionally, the mitigation option reduced the total risk for supplier 1 to 18% from 33% shown in the Total Risk node and the penalty cost for $10,000 decreased below 10%. The final updated Bayesian network is depicted in Figure A3, which can be found in Appendix A. The updated Primary Criteria nodes for Supplier 1 and Supplier 2 are illustrated in Figure 5.11a and Figure 5.11b, respectively.

Scenario 3: Supply chain management wants to compare the outcome of the supplier selection process by enabling all mitigation nodes to see which supplier yields the better likelihood of on-time delivery. By doing so the total mitigation cost for both suppliers results in $35,000 for Supplier 1 and \$15,000 for Supplier 2. Deploying all mitigation strategies also reduces the risk for Supplier 1 to 13% and for Supplier 2 to 60%. Despite the total mitigation cost for Supplier 1 being higher, the supplier selection process in the Bayesian network still favors Supplier 1 in terms of total risk as illustrated in Figure A4 found in Appendix A. The updated Primary Criteria nodes for Supplier 1 and Supplier 2 are illustrated in Figure 5.12a and Figure 5.12b, respectively.

The outcomes for the scenarios listed above are arranged in Table 5.6. The ability to select the mitigation options enables the decision makers with reasoning strategies by observing how the addition of new evidence propagates throughout the Bayesian network. There are a number of combinations and strategies that the network can be used for to aid in decision making. For example, suppose supply chain management is willing to absorb the risk and financial penalties of one supplier given that the mitigation costs are too high. This and more can be readily implemented into a Bayesian network to help reduce the uncertainty supply chain management faces when dealing with supply chain risks.

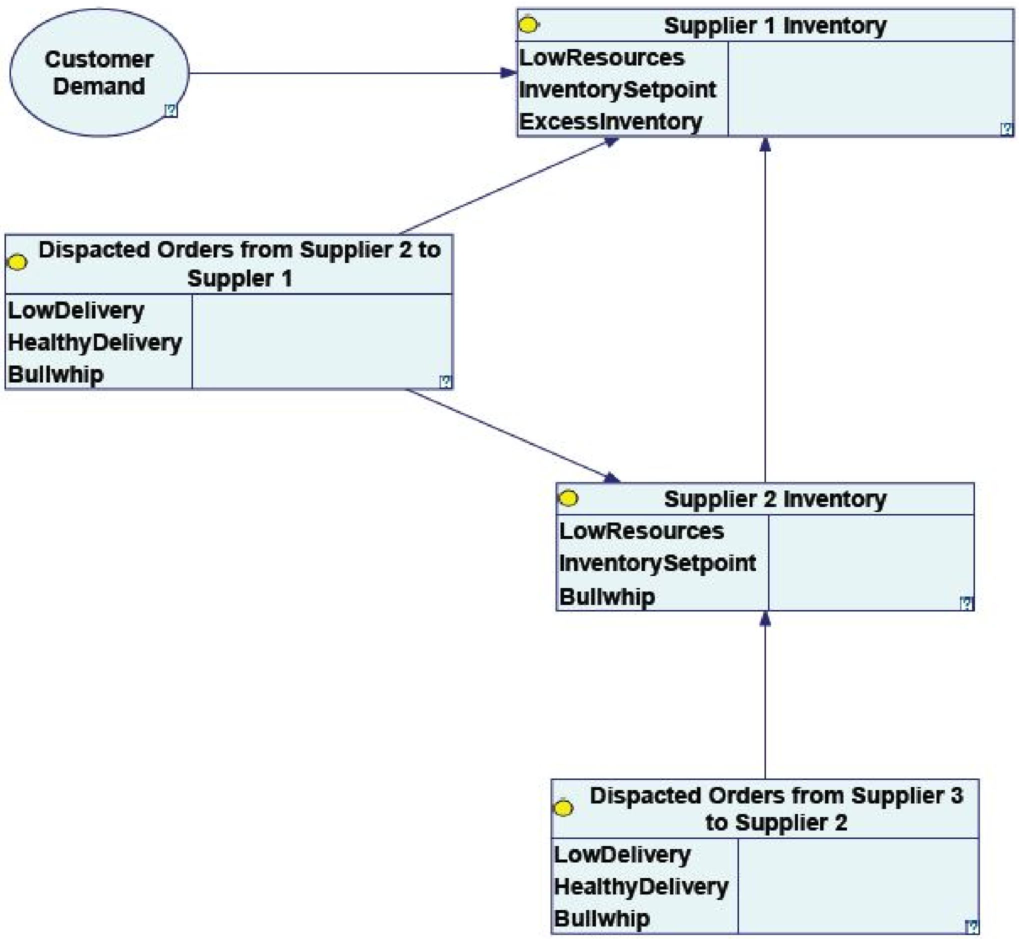


Figure 5.7: Bayesian network constructed for the three-tier inventory supply chain that was trained on the two sets of synthetic data.

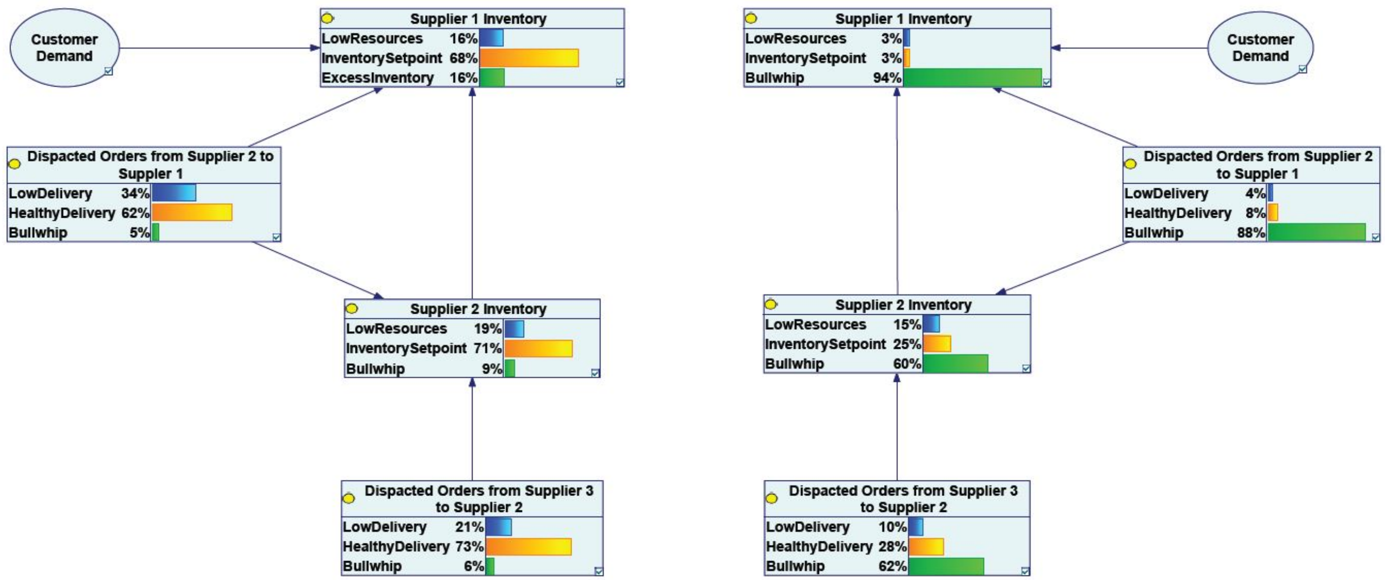


Figure 5.8: Updated Bayesian network constructed for the three-tier inventory supply chain that was trained on the two sets of synthetic data.

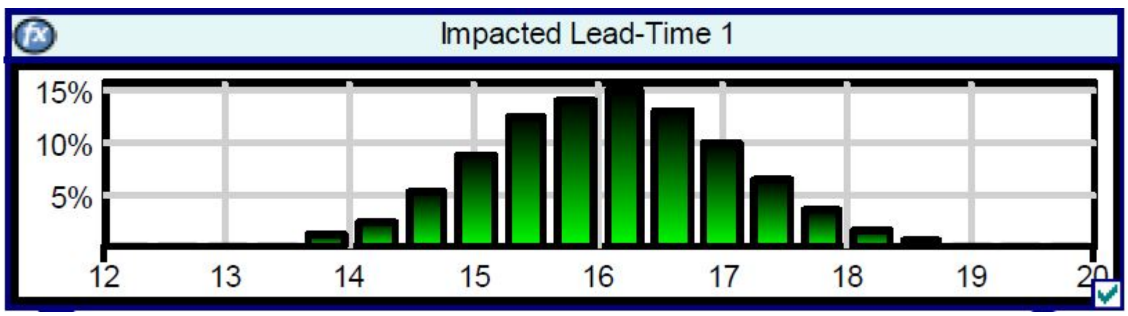


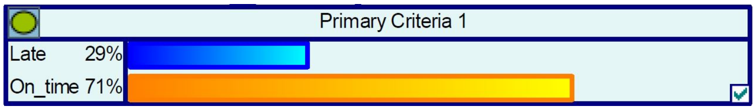
Figure 5.9: The TNorm function implemented in GeNIe for a lead-time distribution.

Table 5.4: Conditional probability table (CPT) for the likelihood of risks occurring conditioned on mitigation options.

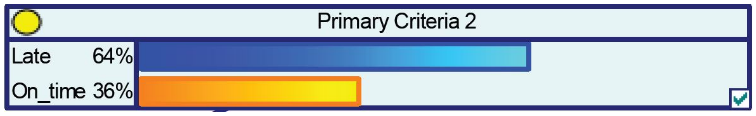
	Quality Risk				Transportation Risk			
	Supplier 1		Supplier 2		Supplier 1		Supplier 2	
	Option_Yes	Option_No	Option_Yes	Option_No	Option_Yes	Option_No	Option_Yes	Option_No
RiskOccurring	0.05	0.08	0.42	0.62	0.02	0.03	0.54	0.6
NoRisk	0.95	0.92	0.58	0.38	0.98	0.97	0.46	0.4

Table 5.5: If-statements coded in the equation nodes to propagate the impact of risk events onto the lead-time for Supplier 1 and Supplier 2.

	Supplier 1	Supplier 2
Quality Lead-Time Impact	If(Quality Risk=”Risk Occurring”,1,0)	If(Quality Risk=”Risk Occurring”,5,0)
Transportation Lead-Time Impact	If(Transportation Risk=”Risk Occurring”,0.5,0)	If(Transportation Risk=”Risk Occurring”,3,0)

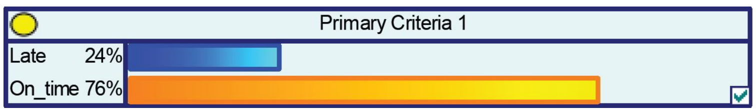


(a) Primary criteria node with updated inference for suppler 1.

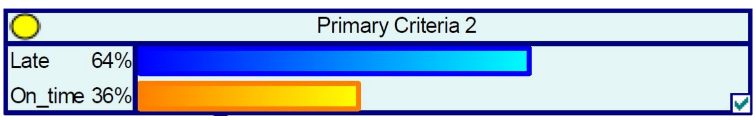


(b) Primary criteria node with updated inference for suppler 2.

Figure 5.10: Updated *Primary Criteria* nodes for Scenario 1.

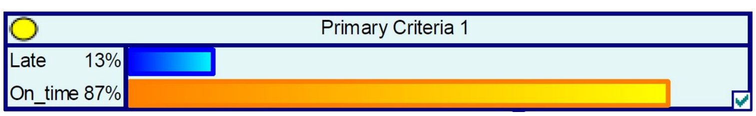


(a) Primary criteria node with updated inference for suppler 1.

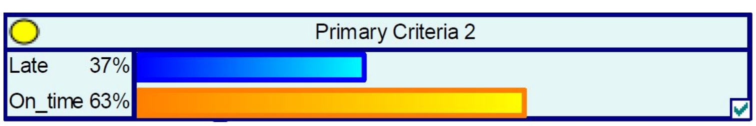


(b) Primary criteria node with updated inference for suppler 2.

Figure 5.11: Updated *Primary Criteria* nodes for Scenario 2.



(a) Primary criteria node with updated inference for suppler 1.



(b) Primary criteria node with updated inference for suppler 2.

Figure 5.12: Updated *Primary Criteria* nodes for Scenario 2.

Table 5.6: Updated Bayesian network results for scenarios when evaluating the risk associated with on-time delivery.

		Total Risk	Total Penalty Cost	Total Mitigation Cost	On-time Delivery
Scenario 1	Supplier 1	33%	\$0 at 60% \$10,000 at 40%	\$0	71%
	Supplier 2	82%	\$0 at 15% \$50,000 at 50% \$100,000 at 35%	\$0	36%
Scenario 2	Supplier 1	18%	\$0 at 90% \$10,000 at 5% \$20,000 at 5%	\$5,000	76%
	Supplier 2	82%	\$0 at 15% \$50,000 at 50% \$100,000 at 35%	\$0	36%
Scenario 3	Supplier 1	13%	\$0 at 99% \$50,000 at ¡1% \$20,000 at ¡1%	\$35,000	87%
	Supplier 2	60%	\$0 at 25% \$50,000 at 53% \$100,000 at 22%	\$15,000	63%

5.3 Bayesian Network Construction for Low-Volume, High-Value Supply Chains

Low-volume, high-value (LVHV) supply chains consist of components that are typically customized to the customer's specifications down to the raw materials used to create the product. These type of components belong to the manufacturing process defined as make-to-order (MTO). Typically, the components under the MTO process are complex due to the engineering requirements set by the customer, leading to long lead-times that are sensitive to supply chain risks. Additionally, the complexity in design and quality results in a limited number of suppliers and basic services for production, furthering the challenges in LVHV supply chains. As the number of suppliers and basic services reduce, then the supply chain is more vulnerable to risks since fewer suppliers are qualified to meet strict requirements. Therefore, LVHV supply chains are more prone to risk events and require advanced monitoring techniques to mitigation risks and improve reliability.

5.3.1 Low-Volume, High-Value Supply Chain Example —- Nuclear Power Plant

The LVHV supply chain and its associated vulnerabilities are found frequently in the nuclear power industry. Since the quantity to produce the product is one or few, with the addition of the product being in a LVHV market, the risk events have greater consequences. The increased magnitude of risk events require additional management strategies because the nuclear industry places high quality and regulatory requirements on suppliers in a already limited supply chain. In the event that a risk occurs due to poor quality or failure to follow regulatory standards, then the product and business suffers the consequence of long lead-times, high costs, and delays. To put this in perspective, the cost of delay in the construction of a nuclear power plant has been estimated at $2 million per day [32]. As a result, proactive risk mitigation techniques must be employed to ensure that suppliers deliver a quality product on time.

In order to implement mitigation strategies and reduce risk for decision makers in the nuclear power industry, a Bayesian network is constructed to depict the complexities in the LVHV supply chain. The construction of the Bayesian network is performed by mapping the fault-tree analysis method by [74] into a Bayesian network. The fault-tree methodology is built for two supply chains, which are translated into Bayesian networks: (1) a fault-tree analysis for a pressurized water reactor (PWR) around its bill of materials and (2) a fault-tree analysis for a PWR steam turbine thrust bearing bill of materials. Both fault-tree methods contain data for suppliers and likelihood of on-time delivery for each component listed in the bill of materials. The fault-trees, along with the data, are mapped to Bayesian networks where the synthetic data for resource availability regarding the bullwhip effect is integrated into the network and mitigation options are added to help aid decision makers in the supplier selection process.

5.3.2 Nuclear Power Plant Supply Chain through Bill of Materials — Fault-tree Analysis Approach

One strategy in defining the complexity of the low-volume, high-value supply chain that the nuclear power industry consists of is using the bill of materials to organize the components and subcomponents with their competing suppliers. This approach used the PWR bill of materials to model a fault-tree for supplier unreliability given supply chain data [73]. The PWR still remains as a point of interest due to recent construction and their prevalence in the current U.S. nuclear power generating fleet. Therefore, the PWR with its bill of materials, and supply chain data used in this model is the basis for this research. Additionally, the fault-tree analysis from [73] provides the foundation for Bayesian network mapping in this research.

The bill of material is initially refined into the eight major components that create the PWR, for example, the reactor vessel and steam turbine are listed as separate items. The bill of materials in full for the PWR is listed in Figure 5.13. The supply chain takes the perspective of the construction company responsible for sourcing the primary goods and services for the PWR. From this perspective, the eight components listed in the PWR bill of materials consists of 11 suppliers. Table 5.7 lists the suppliers (i) with their associated service and the supplier's unreliability (u_i). The supply chain data in this table reflects the unreliabilities experienced within the nuclear industry.

Using the PWR bill of materials and the supply chain data, fault-trees are constructed to represent an event or series of events in the supply chain whose occurrence will result in the unreliability of the PWR construction. Fault-tree analysis is based on identifying the likelihood that the system under study will take on an undesired state defined as the Top Event (TE). For this case, the TE is the PWR construction that is based on the identification of supply chain events that cause suppliers to be unreliable in on-time delivery. The construction of the fault-tree begins with the TE and cascades downwards from the events to their causes until failures of basic constituents are reached. The fault-tree structure can be found in Sherwin's work for additional details[73]. The PWR fault-tree is found in Figure A5, which can be found in Appendix A.

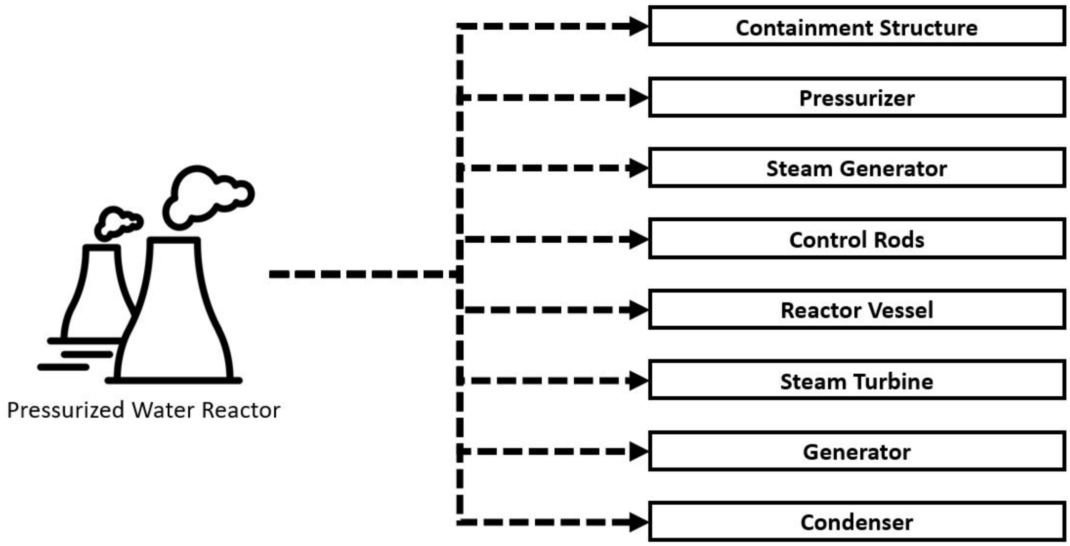


Figure 5.13: The main components in the bill of materials for a Pressurized Water Reactor.

The work presented by Sherwin also included a bill of materials approach for the thrust bearing in a steam turbine. Similarly, the bill of materials for the steam turbine in the PWR is used to develop a supply chain from the perspective of an upstream manufacturer of the steam turbine assembly. From the bill of materials of the steam turbine, the thrust bearing subcomponent is further broken down into its auxiliary components: thrust shoe, bracket, leveling links, and support ring. Figure 5.14 shows the bill of materials for the thrust bearing.

In constructing the fault-tree, the auxiliary components each represent their own TE, which extends upwards to the final TE of the thrust bearing. The events that define the fault-tree analysis consisted of unreliability data obtained from the services each supplier performs in the supply chain process for each auxiliary component. Figure A6 illustrates the high-level fault-tree for the thrust bearing, which can be found in Appendix A. The unreliability data used in the fault-tree analysis defines the probability that a failure will occur at one of the suppliers which prevents on-time delivery. Table A1 in Appendix A lists the suppliers (i) with their associated service and the supplier's unreliability (u_i). The extension of the thrust bearing fault-tree can be found in [73].

With regards to the thrust bearing fault-tree, mitigation strategies are implemented to improve reliability on a supplier while considering the cost to execute them. In one scenario, analysis is performed by either improving or replacing an existing supplier. The existing supplier option improves supplier $i = 13$ by 25%, which costs $37,784 to execute the mitigation strategy. The option to replace an existing supplier removes supplier $i = 13$ and adds supplier $i = 29$. This new supplier has an improved casting source of 0.0947 where this replacement process costs $9,500 to execute. This involves reconstructing the fault-tree in Figure A6 with the improved supplier data. The modified fault-tree and the additional scenarios can be found in [73, 72, 74].

There are serious limitations in fault-tree analysis when modeling complex systems such as the supply chain. Fault-tree analysis is confined to a single event that is dependent on binary outcomes, which can drastically dilute the modeling process of the system under investigation. Additionally, fault-tree analysis is further restricted to only supporting static probabilities as events when in reality the likelihood of events are dynamic and in real-time in nature since the probability distributions are conditioned on additional variables. When applied to supply chain analysis, the fault-tree can only represent inference on a top event and fails to provide decision makers with other important information like financial penalties due to risks or mitigation costs.

It should also be mentioned that in terms of supply chain analysis the addition of mitigation strategies requires extending the fault-tree for each scenario resulting in a number of iterations. This can lead to computationally heavy analysis and procedures. A better representation of modeling uncertainty in probabilistic systems is through Bayesian networks. In fact, previously formulated fault-trees can be translated into Bayesian networks to further exploit their advantages by mapping individual gates with their events to the conditional probability tables (CPTs). For this research, the data provided in [73, 74, 72] is exploited by mapping the fault-trees to Bayesian networks.

5.3.3 Mapping and Verifying Supply Chain Fault-Trees to Bayesian Networks

Fault-tree analysis was originally developed by Bell Telephone Laboratories to evaluate the launch control systems in the mid-20th century[29]. Research has grown to use fault-tree analysis for understanding hazards and failures associated with complex systems. The techniques employed by fault-tree analysis is based on identifying the likelihood that the system under study will take on an undesired state defined as the Top Event (TE). The construction of the fault-tree begins with the TE and cascades downwards from the events to their causes until failures of basic constituents are reached. The methodology is based on the following assumptions: (i) events are binary events; (ii) events are statistically independent; and (iii) relationships between events and causes are represented by means of logical AND and OR gates [55]. Figure 5.15 depicts the undesirable Top Event and its dependency on events, Event A or Event B, through an OR-gate.

Previously formulated fault-trees can be translated into Bayesian networks to further exploit their advantages by mapping individual gates with their events to the conditional probability tables (CPTs). Figure 5.16 shows the mapping of an OR and an AND gate fault-tree into equivalent nodes for a Bayesian network. This approach begins with identifying the probability values assigned to the failure events in the fault-tree, denoted A and B, and mapping them as parent nodes, A and B in a Bayesian network. The TE, denoted C in the fault-tree, is mapped to the child node C in the Bayesian network.

The entries into the CPTs correspond to the *truth tables* governed by the logic from the OR and AND gates. To this end, the CPT entries are either 0's or 1's to satisfy the mapping of the conditional relationship between the risk event nodes and their consequential failures. Additional derivations and examples can be found in [9]. To this end, the mapping is performed on the fault-trees presented in Section 5.3.2 for the PWR bill of materials supply chain and the steam turbine thrust bearing bill of materials supply chain.

The PWR fault-tree and thrust bearing fault-trees with mitigation strategies are mapped to Bayesian networks and are shown in Figure A7 and Figure A8, respectively, which can be found in Appendix A. In order to verify that the mapping is performed successfully, the top event unreliability for the PWR fault-tree and steam turbine thrust bearing fault-tree is compared to the updated Bayesian network in scenarios listed below.

Scenario 1: PWR Fault-Tree and Updated Bayesian Network Inference: The original fault-tree analysis for the PWR yields an unreliability of 0.1215 [74]. In other words, there is a 12.15% probability that there exists one fault from the suppliers supporting the manufacturing process of the PWR resulting in a failure to deliver the component on-time. In the Bayesian network, the likelihood that the PWR will not be delivered on-time, according to node Pressurized Water Reactor, is 12% as shown in Figure 5.17. The full Bayesian network is illustrated in Figure A7, which can be found in Appendix A.

Scenario 2: Thrust Bearing Fault-Tree and Updated Bayesian Network: The fault-tree analysis from [73] indicates that the supply chain has a 66.92% probability that there exists one fault from the suppliers supporting the thrust bearing manufacturing process thus resulting in a failure to deliver on-time. In the Bayesian network, the likelihood that the thrust bearing will not be delivered on-time, according to node Thrust Bearing Criteria, is 67% as shown in Figure 5.18. The full Bayesian network is illustrated in Figure A8, which can be found in Appendix A.

Scenario 3: Risk Mitigation Thrust Bearing Fault-Tree and Updated Bayesian Network: In [73], risk mitigation cases were studied by modifying the fault-tree for a comparison of either improving supplier $i = 13$ or replacing supplier $i = 13$ with improved supplier $i = 29$. Both strategies result in a final unreliability of 65.72% with a cost of $37,784 for improving existing supplier $i = 13$ and $9,500 to replace the existing supplier with the new one.

In the Bayesian network, evidence-based nodes can be implemented to graphically depict mitigation strategies and their associated costs. When the Improve Existing Supplier node is selected then the cost to execute the strategy is propagated to the Mitigation Cost node, which shows $37,784. Deploying the mitigation strategy impacts the final unreliability, which matches the fault-tree analysis of 65% as shown by the Thrust Bearing Criteria . This mitigation strategy is illustrated in Figure 5.19.

On the other hand, when the Replace Existing Supplier node is selected then the cost to execute the strategy is propagated to the Mitigation Cost node, which shows $9,500. Deploying the mitigation strategy impacts the final unreliability, which matches the fault-tree analysis of 65% as shown by the Thrust Bearing Criteria. This mitigation strategy is illustrated in Figure 5.20.

The network successfully determines the mitigation strategies generated in [73]. The ability to implement all mitigation strategies in one graphical network, along with their costs, highlights the strengths of Bayesian networks. All mitigation strategies analyzed in [73] are implemented in this research in the final Bayesian network illustrated by Figure A9, which can be found in Appendix A.

In this research, the PWR Bayesian network and the thrust bearing Bayesian network are combined to create the final network. The final Bayesian network reduces the uncertainty supply chain decision makers face when performing the supplier selection process. The final Bayesian network illustrates a supply chain whose perspective is from the construction company responsible for sourcing the primary goods and services for the PWR. The reason for integrating both networks is to reduce in uncertainty in the supply chain process by including upstream supplier information. When integrating the two networks, synthetic data is used to reflect unreliable delivery time of certain components. Additionally, the mitigation strategies proposed by [73] are included in the final network as well as resource availability nodes that are trained on the synthetic data generated in Section 4.3.

Table 5.7: Suppliers and their unreliability to provide the goods and/or services for the main components of a pressurized water reactor.

Supplier (i)	Good and/or Service	Supplier Unreliability (u_i)
1	Containment Structure	0.0031
2	Pressurizer	0.0236
3	Steam Generator	0.0489
4	Control Rods	0.023
5	Control Rods	0.0215
6	Reactor Vessel	0.0441
7	Reactor Vessel	0.0263
8	Turbine	0.0347
9	Generator	0.0088
10	Condenser	0.0288
11	Condenser	0.0411

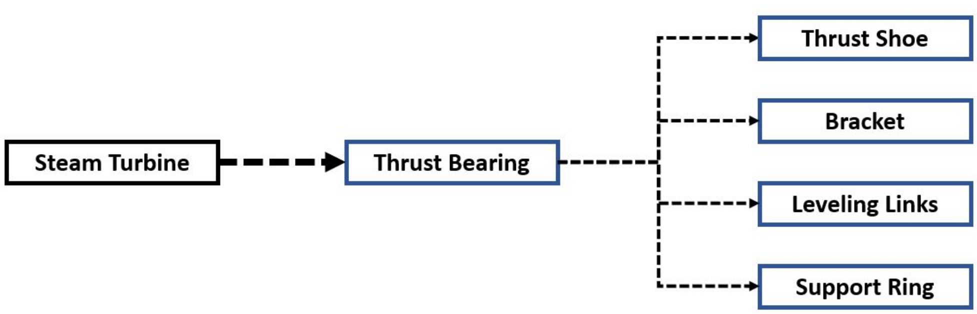


Figure 5.14: Bill of materials for a thrust bearing that is used in the construction of a PWR steam turbine.

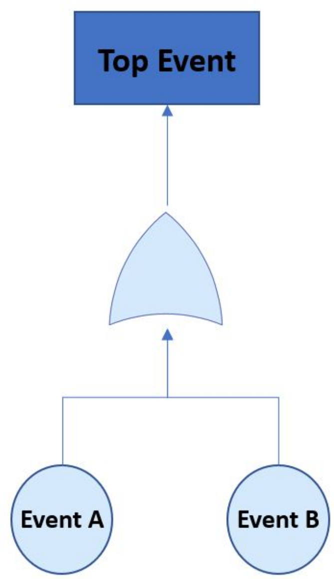
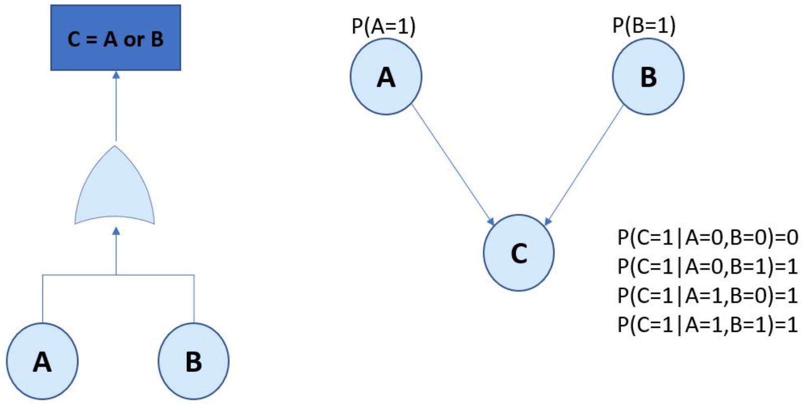
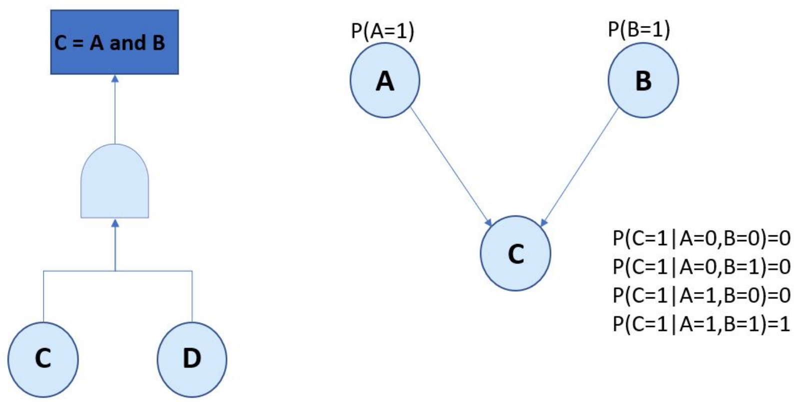


Figure 5.15: A simple fault-tree where the top event is dependent on an OR-gate of Event A or Event B.



(a) Fault-tree to Bayesian network mapping for an OR-gate.



(b) Fault-tree to Bayesian network mapping for an AND-gate.

Figure 5.16: Fault-tree to Bayesian network mapping for a top event, C, that is dependent on events A and B.

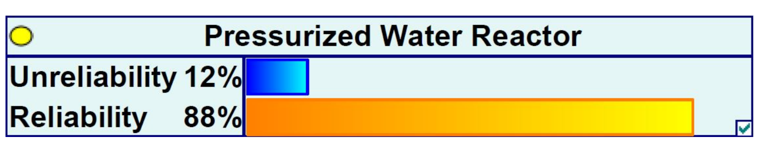


Figure 5.17: Updated *Pressurized Water Reactor* node from mapped Bayesian network.

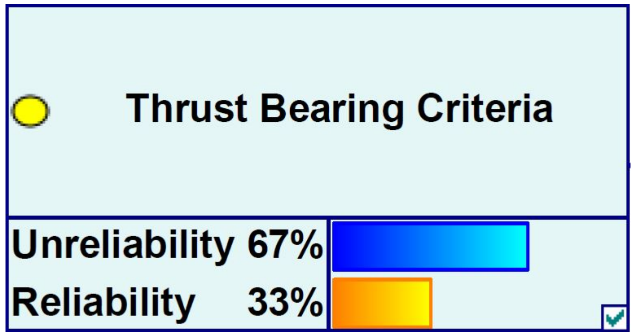
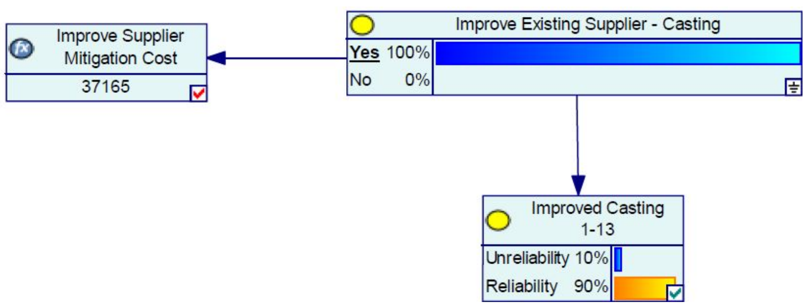
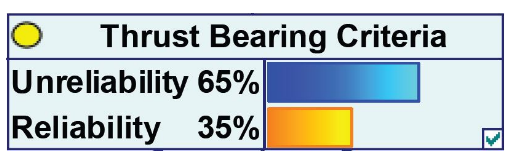


Figure 5.18: Updated *Thrust Bearing Criteria* node from mapped Bayesian network.

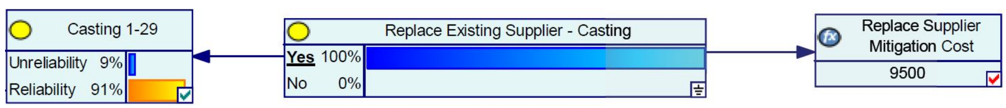


(a) Mitigation strategy for improving an existing supplier with its associated cost.

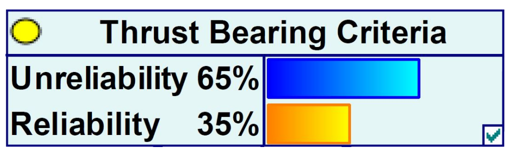


(b) Updated inference on the thrust bearing reliability when improving an existing supplier strategy is deployed.

Figure 5.19: Thrust bearing criteria when an improve supplier mitigation strategy is deployed.



(a) Mitigation strategy for replacing an existing supplier with its associated cost.



(b) Updated inference on the thrust bearing reliability when replacing an existing supplier strategy is deployed.

Figure 5.20: Thrust bearing criteria when replacing an existing supplier mitigation strategy is deployed.

5.4 Particle Filter Inventory Data Integration for Estimated Resource Availability

In Section 4.3, state-estimators were developed to estimate the inventory positions of the synthetic inventory data from a low-volume, high-value (LVHV) make-to-order/ship-to-stock (MTO/STS) supply chain model. The data produced from the model is used as a training set for Bayesian network learning to be performed. Bayesian network learning uses the training data to provide probabilistic inference on hypotheses by populating the CPTs of a resource availability model within the Bayesian network. This process is outlined in Figure 5.21.

GeNIe has the capability of generating the CPTs for a model given there is suitable data for learning. Bayesian network learning is a probabilistic approach to building models, which combines prior knowledge with learning from data. In order to do so, a Bayesian network depicting the LVHV supply chain is constructed. The constructed Bayesian network shows how the input demand has a conditional relationship between the dynamics of the MTO system and the STS system with respect to production, inventory, back-order rate, and order-book status. This Bayesian network is shown in Figure 5.22. The goal of this network is to determine if resources are available throughout the supply chain given the inventory-production data of the MTO upstream supplier.

Two Bayesian networks were created from the two sets of synthetic data: (1) a network that provides the likelihood of available resources given a set of data whose model was not impacted by the step input demand and (2) a network that provides the likelihood of available resources given a set of data that was impacted negatively by the step input demand simulating the bullwhip effect. The synthetic data is discretized into states using GeNIe. For this research, the node that is used for resource availability estimation is the *Backorder Rate* node of the STS system. The Backorder Rate contains three states as a measure of the rate of backorders in the STS system: (1) DecreasingBORATE indicating that the back orders are decreasing and that STS system is shipping their resources to the downstream MTO supplier, (2) HealthyBORATE defining that the order rate matches the amount of resources being shipped to the downstream MTO supplier, and (3) IncreasingBORATE defining that the number of requested goods are not meeting production and backorders are accumulating thus the downstream MTO supplier is not receiving any resources. Figure 5.22 shows both Bayesian networks.

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 [43]. GeNIe has the ability to automatically update beliefs in the network to provide a probabilistic inference to aid

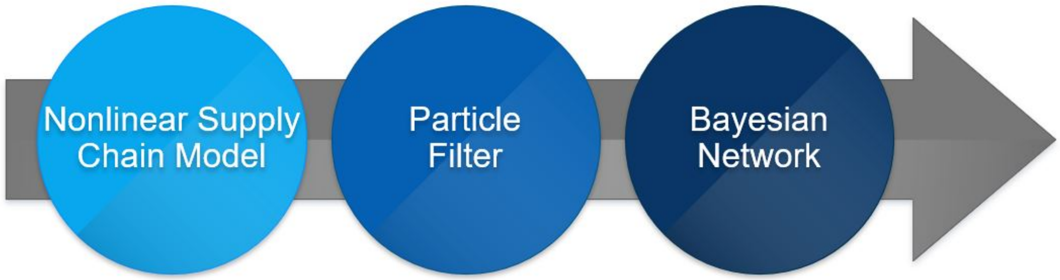


Figure 5.21: Process of integrating the synthetic data, particle filter, and Bayesian network model.

decision makers when considering their goals. Figure 5.23 shows the updated GeNIe results for the resource availability Bayesian network. These networks are later integrated into the final Bayesian network.

The updated networks provide a probabilistic inference on whether the upstream MTS system has a healthy level of backorders. The network on the right illustrated in Figure 5.8 learned from the data set that contained typical behavior thus resulting in a 66% probability that the backorders are healthy. This learned Bayesian network inventory-production model is integrated into the final network as a mitigation strategy where a new supplier is introduced to depict risks involving resource availability.

On the other hand, the network on the left illustrated in Figure 5.8 learned from the data set that contained bullwhip impacted data. This results in a 69% likelihood that backorders are accumulating, implying that the upstream MTS supplier may have been impacted by the bullwhip effect resulting in an inability to satisfy incoming demand. This learned Bayesian network inventory-production model is integrated into the final network as a mitigation strategy where a new supplier is introduced to depict risks involving resource availability.

Additionally, particle filtering methods produce the posterior distribution of the model discussed in Section 4.3. These were represented by the histograms and probability density functions for several states. The benefit of having the posterior distributions is that they can be used directly in the Bayesian network for inferring risk associated with resource availability. To this end, an additional Bayesian networks was created from the probability distributions that infers available resources given posterior distributions from a healthy synthetic data set.

The Bayesian network is constructed to estimate the inventory levels of upstream suppliers given the posterior distributions generated from the particle filter. Estimation of the resources of the upstream supplier is achieved by training the Resource Availability node with the posterior distributions. Since the model generated data for 52 weeks, the inventory is averaged for quarterly generated data. The reason for choosing an averaged quarterly estimate is to reduce the computational effort in creating the final Bayesian network.

The Resource Availability node is dependent on an evidence-based Quarterly Report node. This node can take on four states: (1) First Quarter, (2) Second Quarter, (3) Third Quarter, and (4) Fourth Quarter. When the node is provided evidence for one of the states, the probability distribution for that quarter is inferred in the final network. The final generalized Bayesian network is illustrated in Figure 5.24.

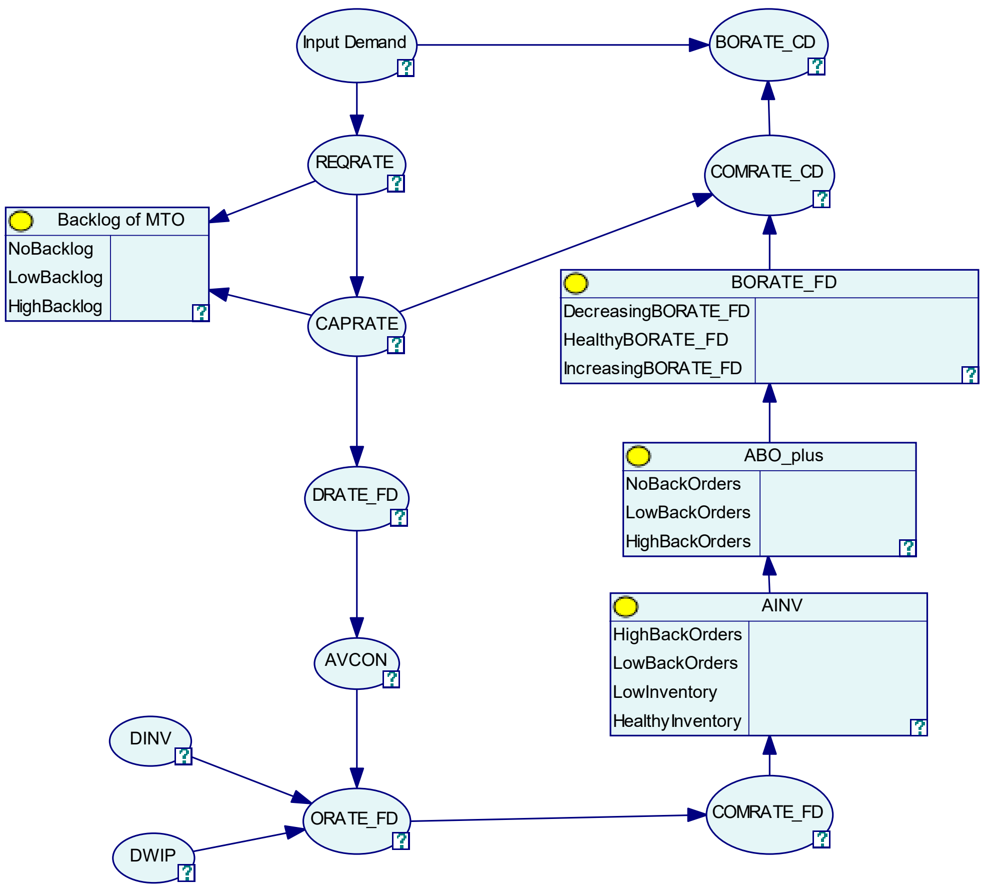


Figure 5.22: Bayesian network constructed for the MTS/MTO hybrid supply chain that was trained on the two sets of synthetic data.

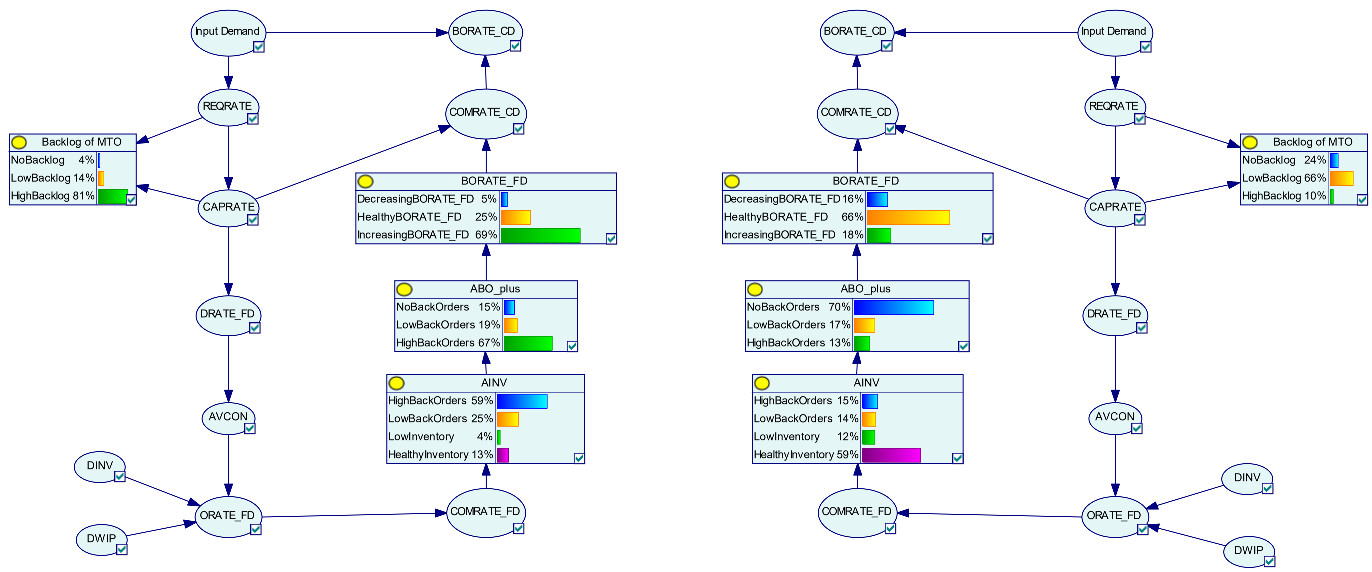


Figure 5.23: Updated Bayesian network constructed for the MTS/MTO hybrid supply chain that was trained on the two sets of synthetic data.

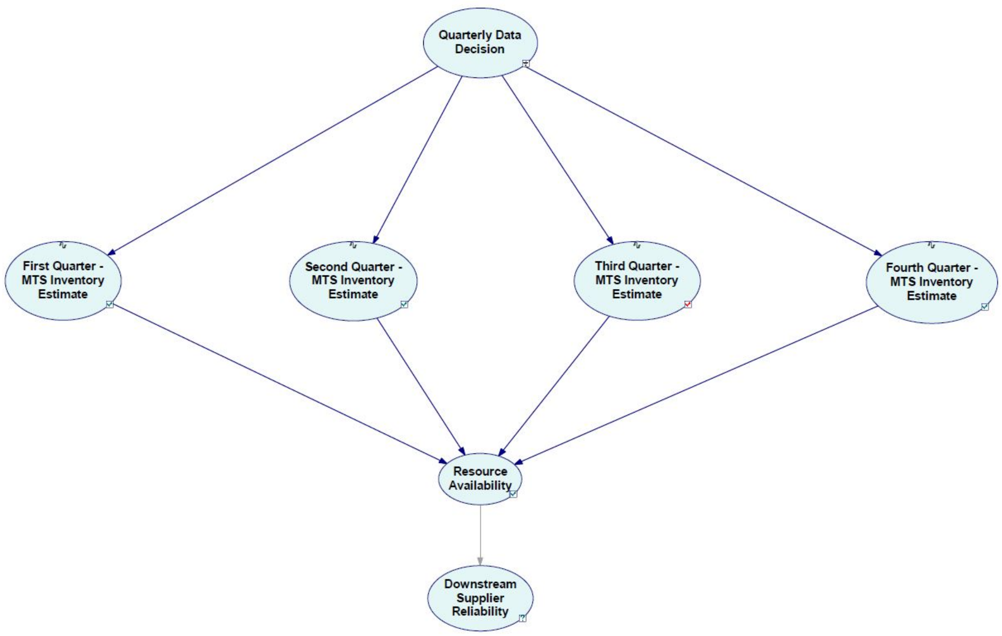


Figure 5.24: Bayesian network constructed for the MTS/MTO hybrid supply chain that was trained on the posterior distributions generated from a particle filter.

5.5 Bayesian Network to Aid Supply Chain Managers in the Supplier Selection Process

The final Bayesian network depicts the supply chain for the manufacturing of the main components for a Pressurized Water Reactor (PWR) and includes the services performed by upstream suppliers in the steam turbine main component by integrating the thrust bearing bill of materials network constructed in the previous section. The final Bayesian network graphically illustrates the PWR supply chain in Figure 5.25. The network aids decision makers in the supplier selection process whose perspective is from the construction company responsible for sourcing the primary goods and services for the PWR. The network also enables decision makers with the visibility of upstream suppliers, which further reduces uncertainty in supply chain risks by estimating likelihoods that may impact the main components of the PWR. Finally, decision makers have the ability to employ mitigation strategies to reduce potential risks to ensure construction of the PWR provided that the main components are delivered on-time.

For the construction of the PWR to begin, its main components must be delivered on-time. This is represented by the PWR Construction node, which can take on two states: (1) On-time Delivery and (2) Late Delivery. The two states in the PWR Construction node are conditionally dependent on the reliability of the suppliers for the main components in the PWR. The suppliers that manufacture the main components are represented by their respective nodes in the network and are identified by their own index, i, as listed in Table 5.7, and the main component they are responsible for manufacturing. The conditional probability tables (CPTs) for the PWR network are a result of the mapping from the fault-tree analysis performed in [74]. Figure 5.25 illustrates the Bayesian network for the PWR bill of materials.

Each supplier can take on two probabilistic states: (1) Reliability and (2) Unreliability. The Reliability state defines the likelihood that the supplier will have no impeding risks occur in delivering the main component on-time. Conversely, the Unreliability state define the likelihood that the supplier will encounter at least one risk that disrupts the delivery of the main component on-time. For example, the likelihood that the supplier that manufactures the steam generator encounters a risk that increases lead-time is 95% as indicated by the Steam Generator node in Figure 5.25.

The PWR network also includes a submodel in the steam turbine component through the Thrust Bearing node, where a submodel node is a special type of node in GeNIe that hosts larger networks and facilitates their own Bayesian network. From the perspective of the supply chain management, this submodel contains upstream suppliers within the supply chain network of the PWR construction. In this research, the Bayesian network is only concerned with the upstream suppliers manufacturing the steam turbine thrust bearing. The conditional probability tables (CPTs) for the thrust bearing network are a result of the mapping from the fault-tree analysis performed in [74]. Inside the Thrust Bearing submodel illustrates the supply chain for the PWR steam turbine, which is depicted in Figure 5.26.

Similar to the PWR bill of materials Bayesian network, the thrust bearing submodel depicts the bill of materials for the constituents of the thrust bearing: leveling links, thrust shoe, bracelet, and the support ring. These constituents are further broken down into the manufacturing processes that for which each supplier is responsible. Each node in the network is labeled by its manufacturing process following by its supplier service index, i. The likelihood for the suppliers in the submodel are defined in the same fashion as the PWR network where each supplier can take either Reliability or Unreliability. The manufacturing processes, supplier indices, and unreliability data is listed in Table A1.

For this research, the network illustrates the supplier selection process within the leveling links subcomponent of the thrust bearing, which is depicted by the Leveling Links Criteria. In the leveling links portion of the Bayesian network, the available resource model is integrated into additional suppliers to depict the benefits of having resource transparency of upstream suppliers in the decision making process. The leveling links portion is also equipped with mitigation strategies where several scenarios are shown to illustrate the benefits of executing evidence-based nodes to reduce risk in the supply chain. The goal of the network is to study how the supplier selection process impacts the reliability of the Thrust Bearing Criteria. Figure 5.27 shows the leveling links portion of the thrust bearing submodel, where the thrust shoe, bracelet, and support ring suppliers are added to their own submodels for convenience.

5.5.1 Mitigation Strategies for Upstream Leveling Links Suppliers

This section describes several case studies involving mitigation strategies and demonstrates how the Bayesian network supports decision making by enabling supply chain professionals the ability to plan, monitor, and control events that may impact the financial goals of the company. For this research, the risk mitigation decisions are performed prior to ordering the component with the goal of reducing the uncertainty in the supplier selection process in the casting manufacturing process for the leveling links. The end goal is to observe how the Thrust Bearing Criteria node changes when the mitigation strategies are added to the supplier selection portfolio.

Scenario 1: In this scenario, an improved supplier Casting 1-30 is added to the supplier portfolio as a mitigation strategy. This improved supplier has an unreliability likelihood of 9.47%, as compared to the original Casting 1-13 unreliability of 12.64%. The introduction of an improved supplier requires the company to engage in a new contract that costs $12,837. When the mitigation strategy is performed, the Improved Replacement Supplier node is updated with the evidence to the appropriate state. When improving the existing supplier the overall Thrust Bearing Criteria improves to 63%. Figure 5.28 highlights the portion of the Bayesian network for this scenario. The full Bayesian network is illustrated in Figure A10, which can be found in Appendix A.

Scenario 2: In this scenario, two casting suppliers are introduced that enabled inventory data sharing with the end customer in the supply chain. The two Bayesian networks created from the sets of synthetic data in Section 5.4 are integrated into the new casting suppliers. The new supplier Casting 1-31 has a conditional dependence on the Backorder Rate whose data favored a healthy inventory system. On the other hand, the new supplier Casting 1-32 has a conditional dependence on the Backorder Rate whose data indicated an inventory system impacted by the bullwhip effect. The CPT for both new suppliers are populated to reflect the reliability of the suppliers given their inventory health.

The supplier evaluation process is performed by enabling evidence in the Resources Supplier for each new supplier, which acts as a switch in propagating the reliability evidence to the Supplier Criteria node. This node is evaluating the likelihood that the casting supplier is reliable for the Casting 1-13 supplier, Casting 1-31 supplier, and the Casting 1-32 supplier. When enabling evidence into the Resources Supplier, the mitigation cost is tabulated in the Resource Data Mitigation Cost node for each of the additional suppliers.

Without any options enabled, the reliability of the Supplier Criteria takes on the likelihood on the Casting 1-13 resulting in the Thrust Bearing Criteria observing a 65% of being late. Figure 5.29a shows supplier *Casting 1-13* with the evidence node to enable the use of the supplier and Figure 5.29b shows the resulting Thrust Bearing Criteria. The full Bayesian network is illustrated in Figure A11, which can be found in Appendix A.

When introducing Casting 1-31 supplier, at the cost of $9,500, the Thrust Bearing Criteria is improved to 61%. Figure 5.30a shows supplier Casting 1-31 being deployed by enabling the mitigation strategy node and Figure 5.30b shows the resulting Thrust Bearing Criteria. The full Bayesian network is illustrated in Figure A12, which can be found in Appendix A.

When supplier Casting 1-32 is enabled, whose data is known to have poor production-inventory management, there is no improvement on the Thrust Bearing Criteria since the supply chain will favor the original casting supplier. This indicates that the transparency in production-inventory data and estimation of upstream inventory environments can improve the reliability of the supply chain. Figure 5.31a shows supplier Casting 1-32 being deployed by enabling the mitigation strategy node and Figure 5.31b shows the resulting Thrust Bearing Criteria. The full Bayesian network is illustrated in Figure A12, which can be found in Appendix A.

Scenario 3: In this scenario, the company introduces supplier Casting 1-33 to its portfolio. This supplier provides historical productivity data that is dependent on the four seasons: summer, fall, winter, and spring. It should also be noted that the supplier's geographical location is in a region that experiences heavy snow fall. The data indicates that unreliability in the winter for the supplier increases from 12.63% to 16% due to low productivity during the holiday season. Additionally, the winter months account for risks that may impede the flow of resources due to poor weather conditions such as heavy snow fall. For the remaining months, the data indicates that the unreliability for the supplier is 9.47%.

The mitigation strategy involves updating the evidence to the ordering season in the Seasonal Data node to avoid any productivity risks. The introduction of the new supplier costs the company $12,500 — which is tabulated in the Seasonal Data Supplier Mitigation Cost. In the event that the casting is performed in the summer months, then the evidence is updated in the Seasonal Data node. This improves the Thrust Bearing Criteria unreliability to 63%. In the event that the casting is performed in the winter months, then the evidence is updated in the Seasonal Data node. Then the unreliability becomes 67% as shown in the Thrust Bearing Criteria. Figure 5.32 highlights the portion of the Bayesian network for this scenario. The full Bayesian network is illustrated in Figure A14 and Figure A15, which can be found in Appendix A.

Scenario 4: In this scenario, the company introduces supplier Casting 1-34 to its portfolio. This supplier has enabled data sharing of its production-inventory process. By recognizing the conditional dependence between Casting 1-34 and the inventory of its upstream supplier, the posterior distributions from the particle filter performed in Section 5.4 is applied to the data. This enables a reasoning strategy for the supply chain professional to determine when may be the most opportune time to order the desired part.

The supply chain professional is attempting to determine if the leveling links order should take place in the first quarter or second quarter of the upcoming year. The mitigation strategy is enabled by updating the evidence in the Downstream Supplier - Casting 1-34 node. The introduction of the new supplier costs the company \$15,000 — which is tabulated in the Resource Data Casting 1-34 Mitigation Cost node. Thereafter, the appropriate quarter in the *Quarterly Data Decision* node is chosen. When the Q1 state is enabled, the Casting 1-34 supplier unreliability is updated to 75%. This decision infers that the Thrust Bearing Criteria unreliability is 66%. When the Q2 state is enabled, the Casting 1-34 supplier unreliability is updated to 61%. This decision infers that the Thrust Bearing Criteria unreliability is 62%. With the distributions of estimated inventories of the upstream supplier, the supply chain professional can determine that the most opportune time to avoids risks for the leveling links casting is during Q2. The Bayesian network for this scenario is depicted in Figure 5.33.

The outcomes for the scenarios listed above, including other mitigation strategies from the Bayesian network, are arranged in Figure 5.34. The ability to select the mitigation options enables the decision makers with reasoning strategies by observing how the addition of new evidence propagates throughout the Bayesian network. There are a number of combinations and strategies that the network can be used for to aid in decision making. For example, suppose supply chain management does not wish to pay for the cost of a contract that would enable resource data sharing to improve the reliability of the thrust bearing. Instead, the decision maker chooses a strategy that fits their budget by replacing the supplier at a lower cost, but is not as effective in reducing the unreliability of the thrust bearing criteria. This and more can be readily implemented into a Bayesian network to help reduce the uncertainty supply chain management faces when dealing with supply chain risks.

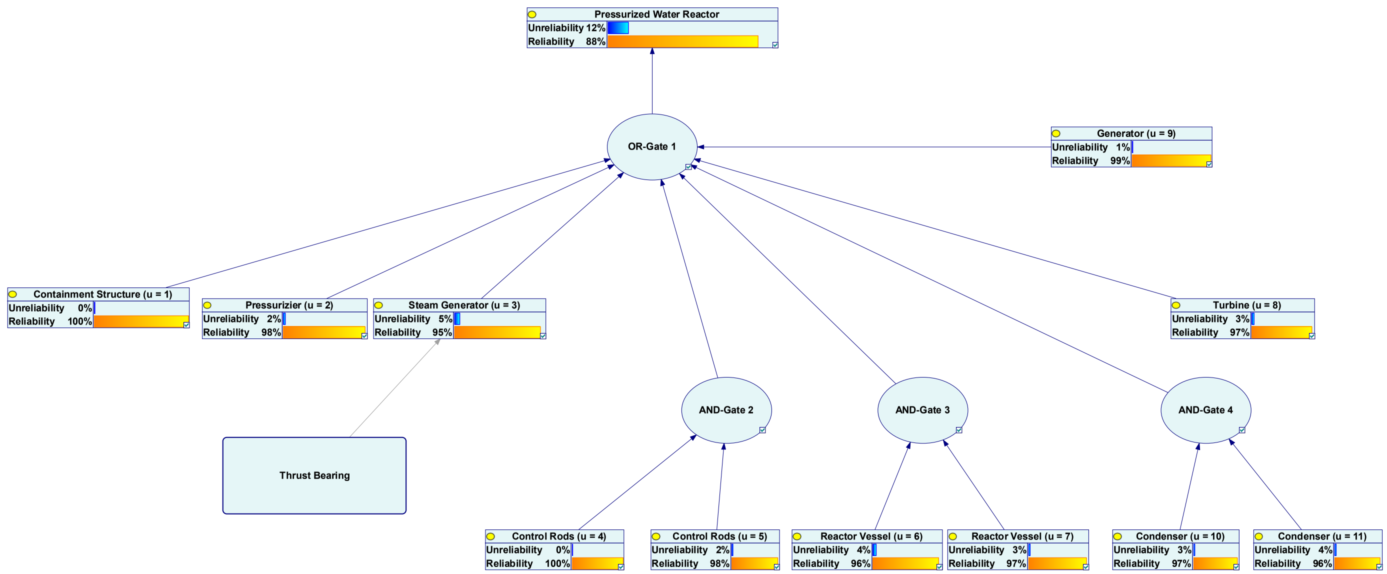


Figure 5.25: Final Bayesian Network supply chain model depicting the bill of materials for a Pressurized Water Reactor.

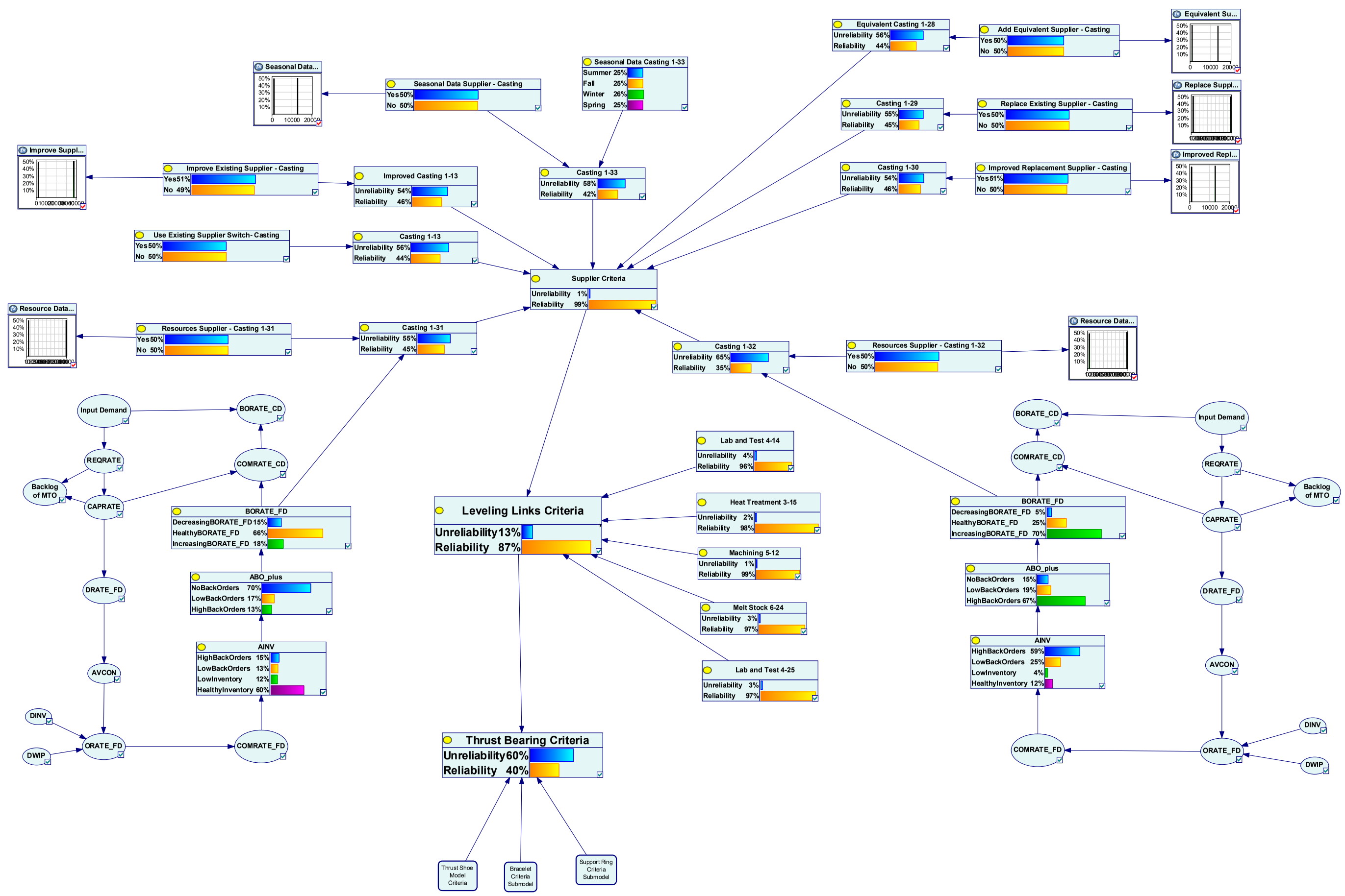


Figure 5.26: Final Bayesian Network submodel of the upstream supply chain depicting the bill of materials for a thrust bearing.

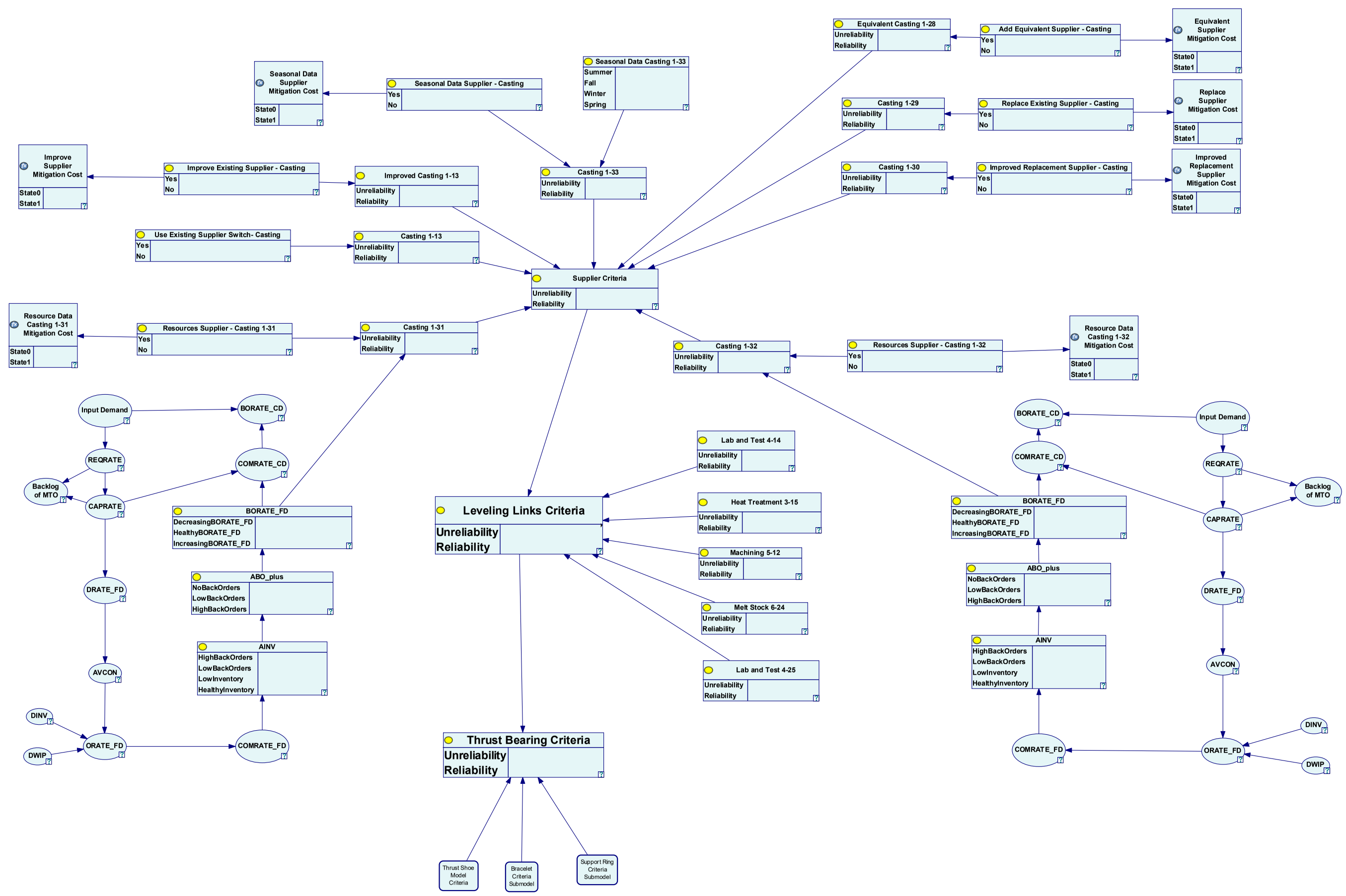
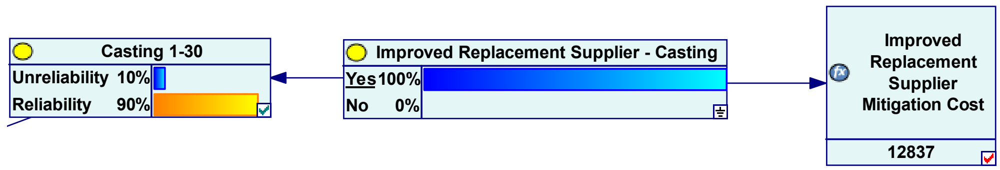
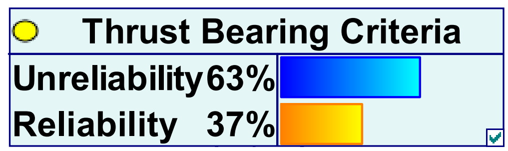


Figure 5.27: Bayesian network portion for leveling links subcomponent.

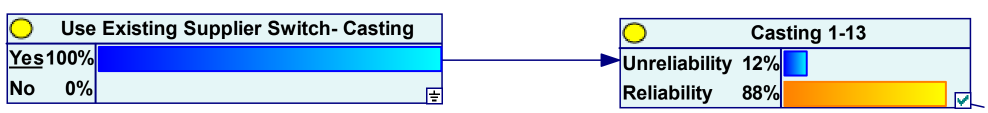


(a) Mitigation strategy for adding an improved supplier with its associated cost.

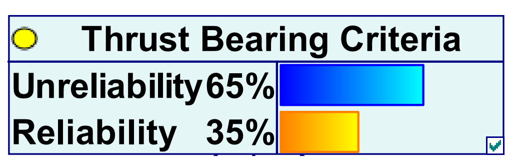


(b) Updated inference on the thrust bearing reliability when an improved supplier strategy is deployed.

Figure 5.28: Adding an improved supplier mitigation strategy and its impact on the thrust bearing criteria.

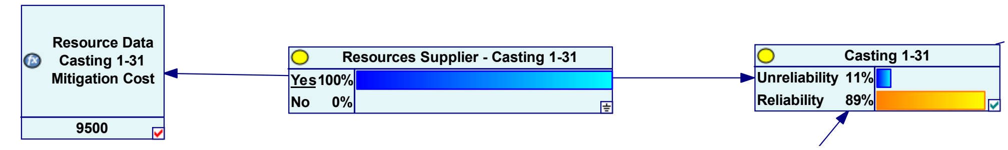


(a) Enabling the original supplier 1-13 through evidence-based nodes in the Bayesian network.

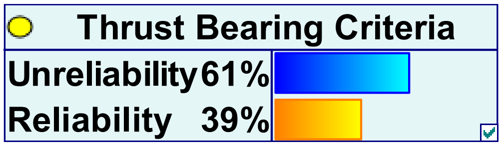


(b) Updated inference on the thrust bearing reliability when the original supplier is used.

Figure 5.29: Thrust bearing criteria when with no mitigation strategies deployed.

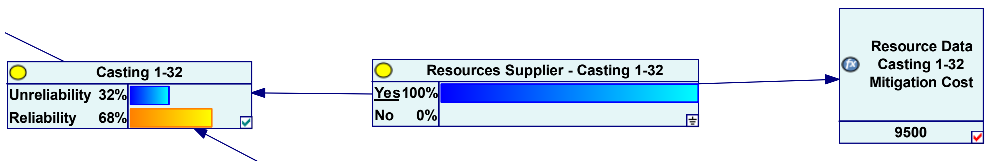


(a) Mitigation strategy for introducing supplier 1-31 who has enabled data sharing.

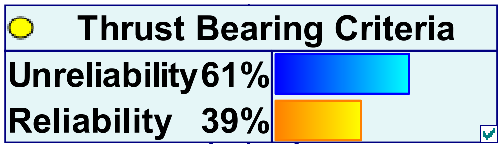


(b) Updated inference on the thrust bearing reliability when the new supplier with data sharing is introduced.

Figure 5.30: Thrust bearing criteria when supplier 1-31 is added to the supplier portfolio.

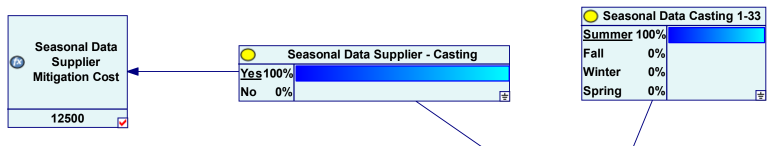


(a) Mitigation strategy for introducing supplier 1-32 who has enabled data sharing.

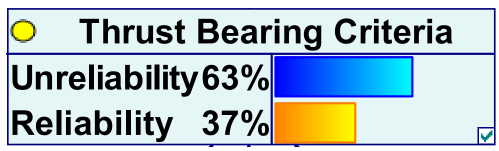


(b) Updated inference on the thrust bearing reliability when the new supplier with data sharing is introduced.

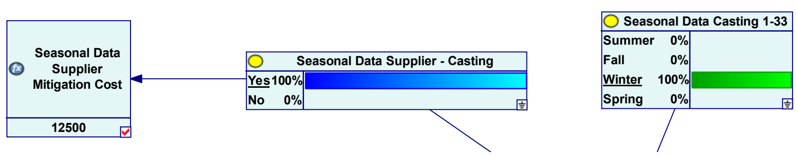
Figure 5.31: Thrust bearing criteria when supplier 1-32 is added to the supplier portfolio.



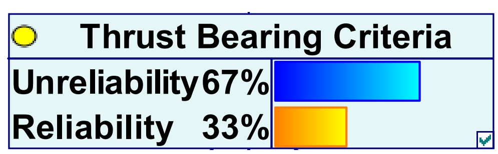
(a) Mitigation strategy for introducing supplier 1-33 and enabling summer seasonal evidence.



(b) Updated inference on the thrust bearing reliability that is dependent on supplier 1-33 in summer months.

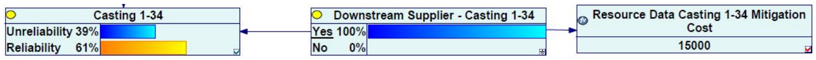


(c) Mitigation strategy for introducing supplier 1-33 and enabling winter seasonal evidence.

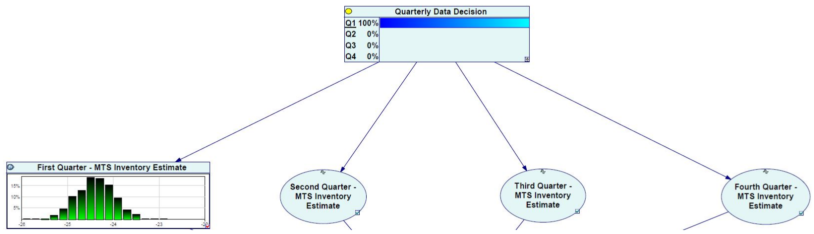


(d) Updated inference on the thrust bearing reliability that is dependent on supplier 1-33 in winter months.

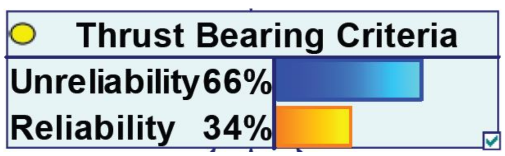
Figure 5.32: Thrust bearing criteria when a new supplier mitigation strategy is deployed that has historical seasonal data on productivity.



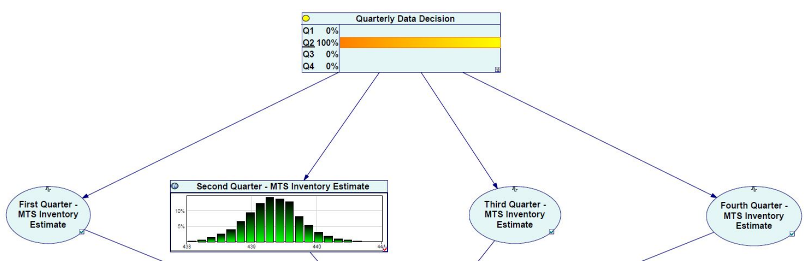
(a) Mitigation strategy for introducing supplier 1-34 and enabling evidence to deploy mitigation strategy.



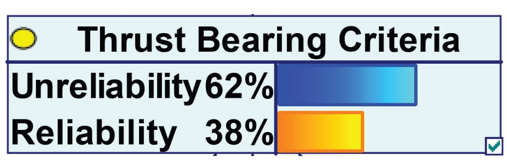
(b) Estimated probability distribution of the upstream supplier for first quarter data.



(c) Updated inference on the thrust bearing reliability that is dependent on supplier 1-34 for first quarter data.



(d) Estimated probability distribution of the upstream supplier for second quarter data.



(e) Updated inference on the thrust bearing reliability that is dependent on supplier 1-34 for second quarter data.

Figure 5.33: Thrust bearing criteria when a new supplier is deployed as a reasoning strategy to estimate resources of upstream supplier.

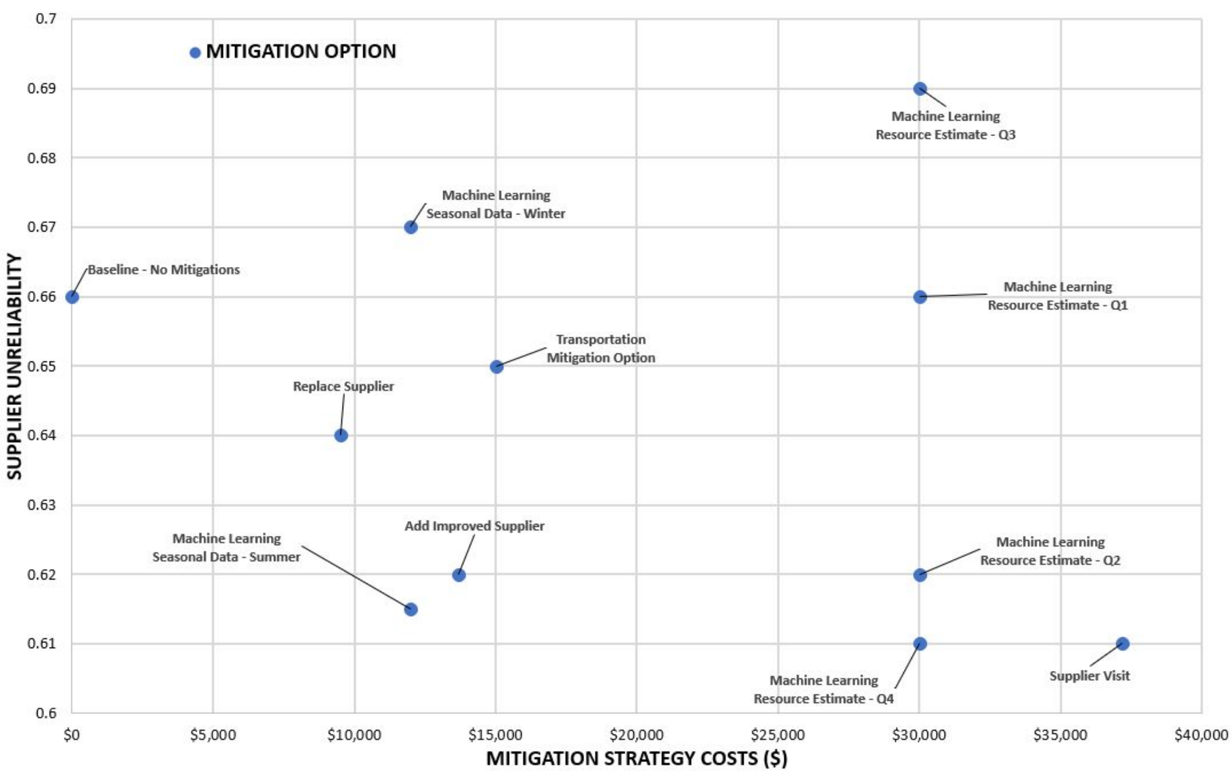


Figure 5.34: Thrust bearing criteria unreliability dependent on mitigation strategies and their deployment cost.

6.0 Summary and Conclusions

6.1 Summary

This research presented a method to reduce the uncertainty decision makers encounter in the supply chain through the use of Bayesian networks. The Bayesian networks illustrated two graphical assessments of supply chain models: (1) series supply chain model for make-to-stock goods and (2) supply chain model for low-volume, high-value nuclear power industry components. Both Bayesian networks were equipped with models of risks, which showed the likelihood of a risk event occurring in the form of directed acyclical graphs. Resource availability was depicted in the network through synthetic data generation from studying the dynamics of inventory-production schemes that are employed in the supply chain. Through the use of state-estimating techniques, resources of upstream suppliers were estimated and the likelihood of a bullwhip effect risk was implemented into the network. In order to counter risks that impeded the goals of the supply chain, mitigation options were illustrated in the networks as evidence-based nodes where strategies could be employed in an attempt to reduce risks.

Risk events were identified in the four areas of the supply chain and implemented into the constructed Bayesian networks. In the production, quality risks were identified as likelihood of the production process not meeting the standards of the company. In the inventory area, the *bullwhip effect* was identified as a phenomena that is caused by a sudden increase in demand, which then causes severe fluctuations in the inventory space of supply chain agents. For the locations, supply chain disruptions were identified through a supplier's historical data that was dependent on the seasons. It was discovered that during the winter months that the supplier was more prone to risk events due to poor weather conditions as determined by their geographical location. Finally, in the transportation, risk events were identified as poor quality in roads, the proximity of the supplier to ports, and weather conditions

The graphical assessment provided by the Bayesian networks enables decision makers in the supply chain the ability to actively monitor their supply chains. This was achieved by identifying what type of risks may occur and their probability of occurring. The planning aspect comes in the form of the mitigation strategies that the decision maker may implement. For both Bayesian networks, scenarios were demonstrated to show how mitigation strategies could be used to employ contingency plans. The scenarios for both Bayesian networks demonstrated how planning a supplier visit can reduce risk events at the cost of sending an employee to ensure quality standards are met. To this end, planning a supplier visit simultaneously satisfied the controlling of risk events by reducing the likelihood of occurrence, 20% for the make-to-stock network and 8% for the low-volume, high-value network. In the low-volume, high-value Bayesian network, a scenario showed when inventory data is shared risk events regarding resource availability can be monitored, planned, and controlled. The scenario with synthetic bullwhip data showed how risk events in resource availability can be avoided through evaluation of the supplier portfolio

The Bayesian networks depicting the supply chains had integrating risk penalties to illustrate the financial consequences if a risk event were to occur. Adding the penalties and accomplishing the previous goals of this research reduces the uncertainty encountered in the decision making process. In particular, by identifying where risks may occur with their associated financial consequence, decision makers had the ability to monitor, plan, and control the events through mitigation strategies. When these strategies were implemented, the likelihood of events decreases thus reducing the likelihood that the financial impact on the supply chain would occur. This was shown for quality assurance strategies through a supplier visit, seasonal strategies for when to order, and through the supplier selection process where the decision maker was able to select from their supplier portfolio the most financially beneficial choice.

6.2 Conclusions

The ability to monitor, plan, and control the uncertainties in the supply chain is an arduous task due to the vast number of events that can lead to disruptions. Decision making under uncertainty is reduced by modeling the supply chain with Bayesian networks. The advantages of Bayesian networks is that they provide an inference on the cause and effect nature that models how events between the interdependent agents in the supply chain propagate throughout the entire network. Through this approach, the Bayesian networks contained probabilistic assessments of disrupting events with integrated resource availability models and mitigation strategies. This enables decision makers the ability to monitor events, update their probability of occurrence given new information, and plan mitigation decisions as a preventative measure to control or reduce the consequences. The use of Bayesian networks ultimately transforms decision making under uncertainty from a

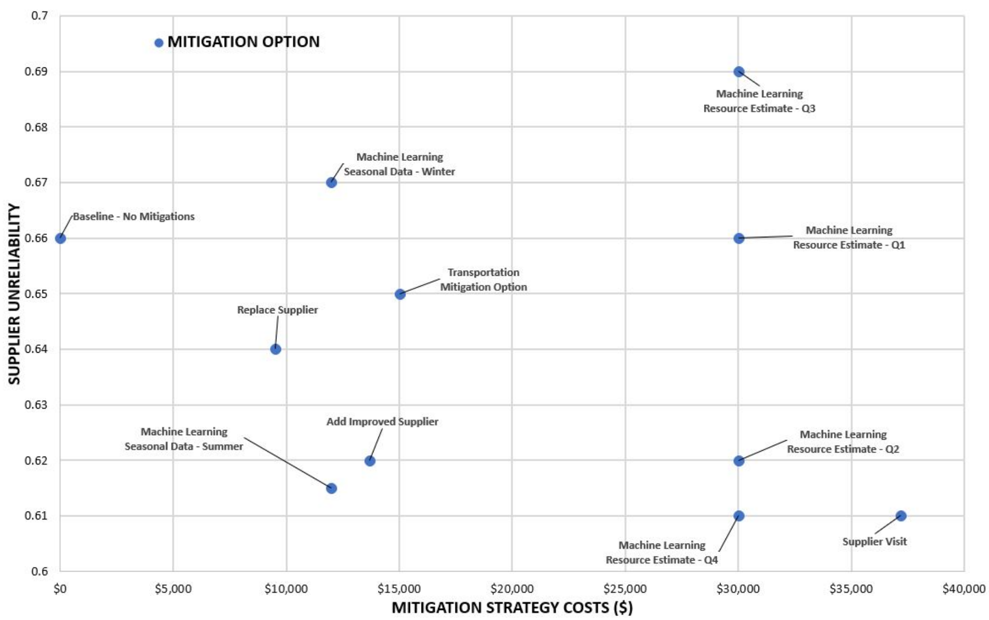


Figure 6.1: Summary of thrust bearing criteria unreliability that is dependent on mitigation strategies and their deployment cost.

reactive approach to a preventative approach by being able to identify strategies that fit within the company's finances.

The outcomes for the scenarios in Section 5.5.1 demonstrated the ability to select mitigation options for decision makers. These mitigation options are scenarios reflecting reasoning strategies by observing how the addition of new evidence propagates throughout the Bayesian network. There are a number of combinations and strategies that the network can be used for to aid in decision making. For example, suppose supply chain management does not wish to pay for the cost of a contract that would enable resource data sharing to improve the reliability of the thrust bearing. Instead, the decision maker chooses a strategy that fits their budget by replacing the supplier at a lower cost, but is not as effective in reducing the unreliability of the thrust bearing criteria. The conclusions to those scenarios are arranged in Figure 6.1. This and more can be readily implemented into a Bayesian network to help reduce the uncertainty supply chain management faces when dealing with supply chain risks.

6.3 Research Contributions

The contributions as a result of the accomplishments presented in this research are identified in the following areas: (1) decision making in the supply chain under uncertainty, (2) resource estimation of upstream suppliers, and (3) nuclear power plant construction.

The contributions made in decision making in the supply chain under uncertainty is accomplished by Bayesian network risk assessment. This research provided the steps necessary to identify the required dynamics to model any supply chain under investigation. By modeling the supply chain with Bayesian networks, risk is assessed through probabilistic occurrences of disrupting events. Understanding how these events impact the supply chain under investigation reduces the uncertainty for decision makers when attempting to satisfy the goals of the company. Therefore, the contribution of reducing uncertainty is accomplished.

This research contributes a method to estimate the inventory of upstream suppliers. By modelling the supply chain through state-space representation, state estimation techniques can provide a probabilistic assessment of upstream inventory count. In the event that resources are available in upstream suppliers, then the likelihood of a delay occurring decreases. This information has the ability to reduce the uncertainty regarding lead-time and aids in decision making for when is the most opportune time to order a component given the estimated likelihood of inventory count.

Advanced nuclear reactor construction can now to be cost effective. This is achieved by modeling the unique characteristics of the industry as a low-volume, high-value supply chain. By modeling the supply chain using the bill of materials and integrating estimated available resources into a Bayesian network, events that can financially harm the construction of nuclear power plants can be avoided through mitigation strategies. When these strategies were implemented, the likelihood of events decreases thus reducing the likelihood that the financial impact on the construction of the nuclear power plant. This was shown for quality assurance strategies through a supplier visit, seasonal strategies for when to order, and through the supplier selection process where the decision maker was able to select from their supplier portfolio the most financially beneficial choice.

6.4 Future Research

The research presented here are the first steps for a data-driven decision model for supply chain analysis. There are several ways to build upon this research:

1. Bayesian network learning through real supply chain data.
2. Implement additional control theory applications to replicate risks in the production-inventory models.
3. Design a decision path with real-time supply chain data to optimize financial goals.

6.4.1 Real Supply Chain Data Set

This research constructed several models to generate synthetic data for inventory-production based systems. Although it was successful, real supply chain data is preferred. The value of real data cannot be replicated and future research could benefit from analyzing all that it has to offer. Real supply chain data could reveal risks not only in the production-inventory system but throughout the entire supply chain network. From the real data, hidden parameters could be estimated to reveal the behavior of the supply chain system, which could then be added to the Bayesian network to determine the likelihood of desired scenarios. Additionally, the use of real data could extend the Bayesian network to include time steps since the data would be dependent on some time series. This would transform the current Bayesian network approach into a dynamic Bayesian network, which would better suit the data and overall analysis of the supply chain.

6.4.2 Modified Models for Synthetic Data Generation

In the event that the future work of this research fails to obtain supply chain data, then the models created to generate synthetic production-inventory data can be updated to reflect real-world scenarios. The models can be updated in two ways: (1) include supply chain agents in parallel of those upstream from the end-customer and (2) include additional delays to account for risks in the production-inventory system. Adding additional supply chain agents in parallel to those upstream from the end-customer would reflect real-world supply chains rather than a simplified series model. This approach would require additional computation efforts to derive the dynamics of the system and ultimately the state-space equations. Including additional delays and control theory techniques to the models can replicate risks in the production-inventory system. For example, a delay function between agents can be implemented to depict a transportation delay. The parameters within this function can be adjusted to reflect risks where transporting resources to downstream suppliers is impacted by any amount of days. This data can then train the Bayesian networks to determine the likelihood of a transportation delay.

6.4.3 Artificial Intelligence for Decision Making

This research successfully aids decision makers in the supply chain, however, human decision making is still flawed by failing to digest all the necessary variables. To overcome this, the future of this research would entail integrating the current model with an artificial intelligence decision model. Reinforcement learning paired with neural networks have been proven successful in environments that are flooded with decisions and an optimal path is required to satisfy a goal. Applying this approach would require decision model inputs and an acute understanding of supply chain goals as operational constraints. Ideally, these inputs and constraints would be identified from supply chain managers through a customer discovery phase. Thereafter, the reinforcement learning coupled with a neural network model could be trained to optimize the supply chain decision making.

Appendix A Supply Chain Bayesian Networks, Fault-Trees, Supply Chain Data, and Difference Equations

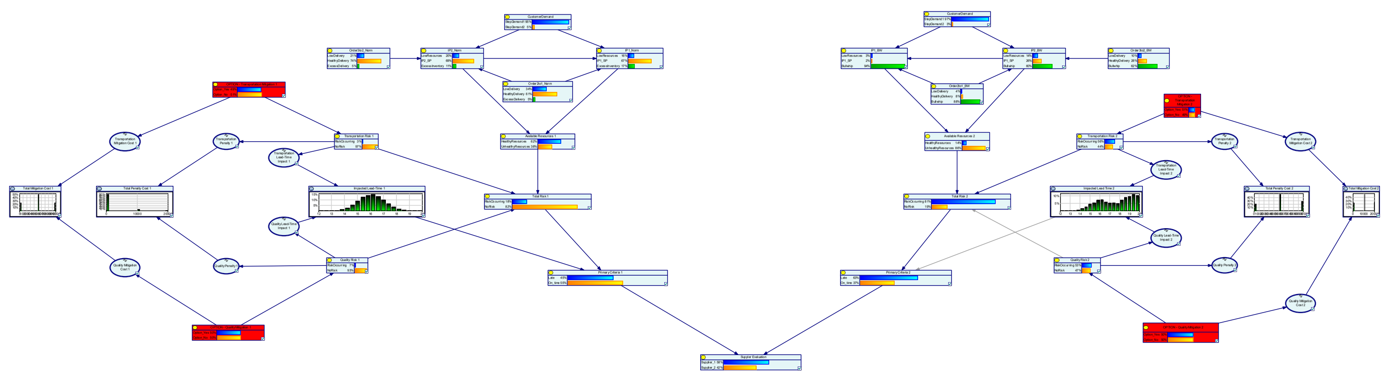


Figure A1: Bayesian network depicting a ship-to-stock component with no mitigation decisions selected.

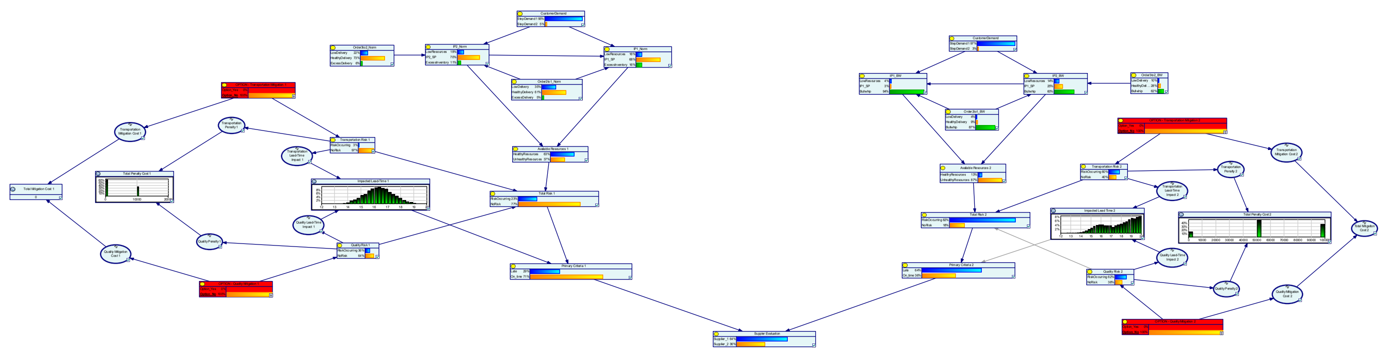


Figure A2: Scenario 1: Updated Bayesian network for the ship-to-stock supply chain with no mitigation options selected.

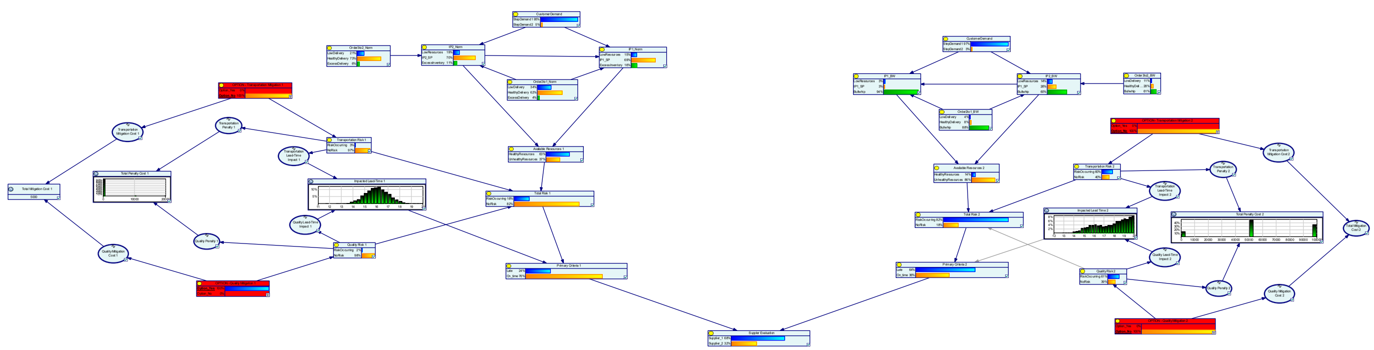


Figure A3: Scenario 2: Updated Bayesian network for the ship-to-stock supply chain with *Quality Mitigation 1* selected.

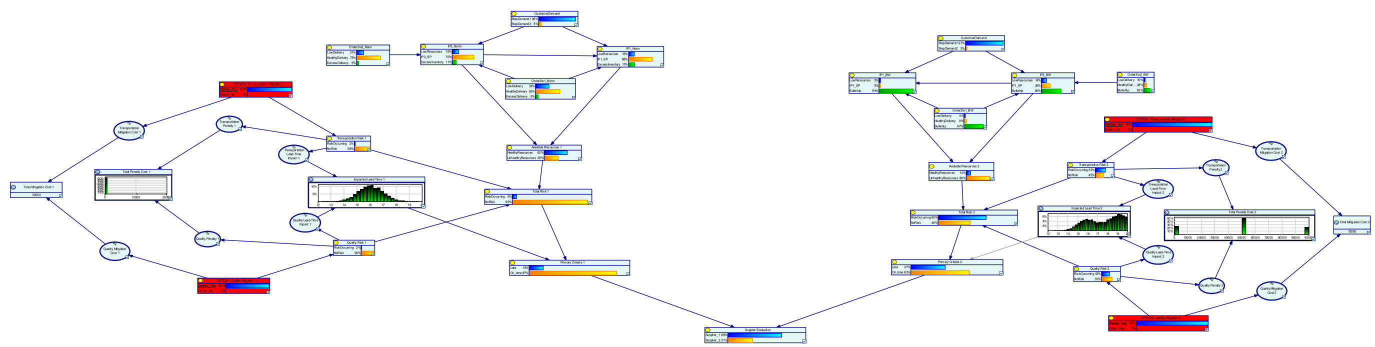


Figure A4: Scenario 3: Updated Bayesian network for the ship-to-stock supply chain with all mitigation options selected.

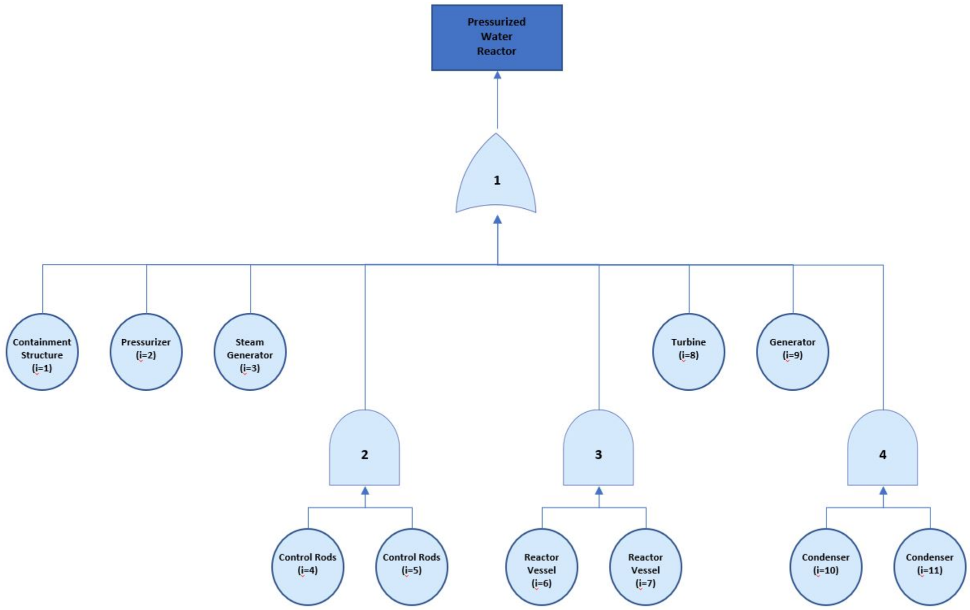


Figure A5: Fault-tree for a pressurized water reactor using its bill of materials.

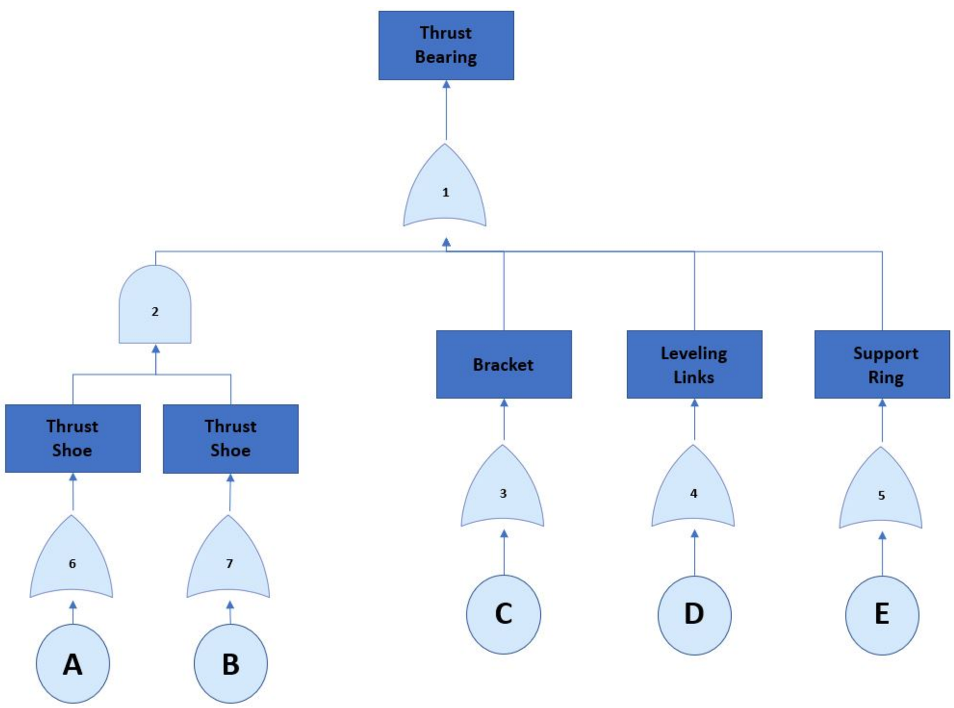


Figure A6: Fault-tree for a pressurized water reactor using its bill of materials.

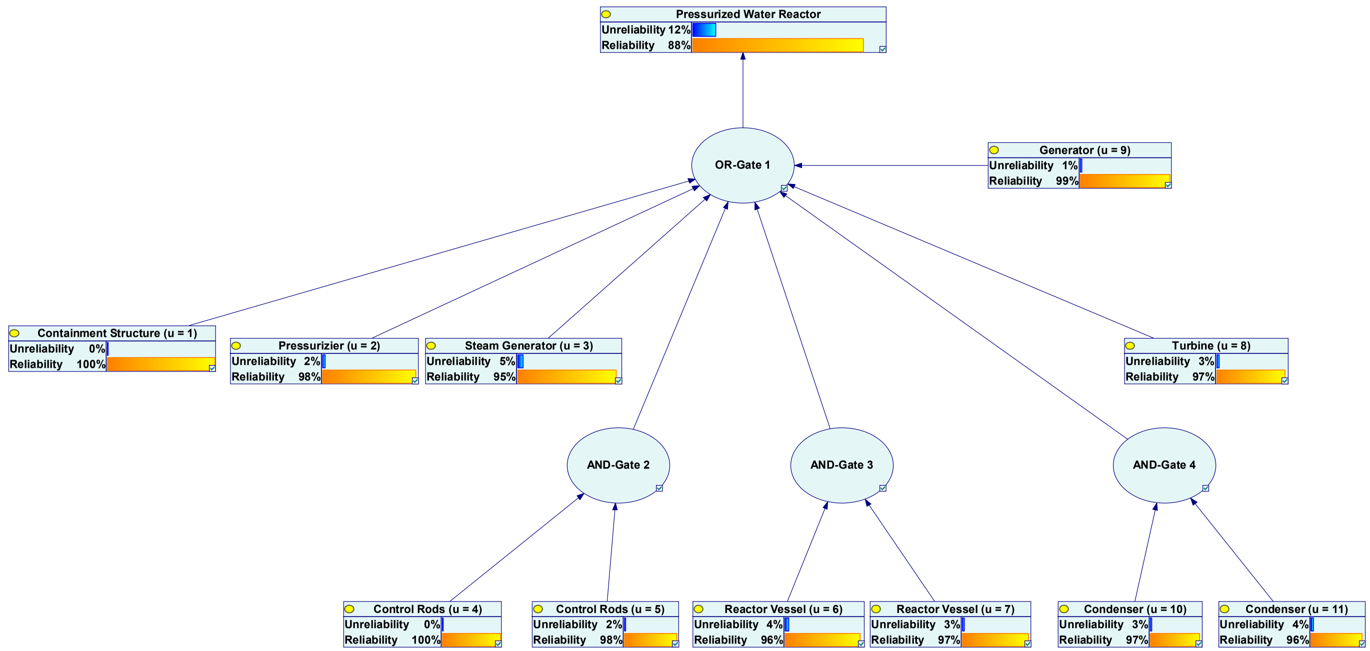


Figure A7: Updated Bayesian network that was mapped from a pressurized water reactor fault-tree.

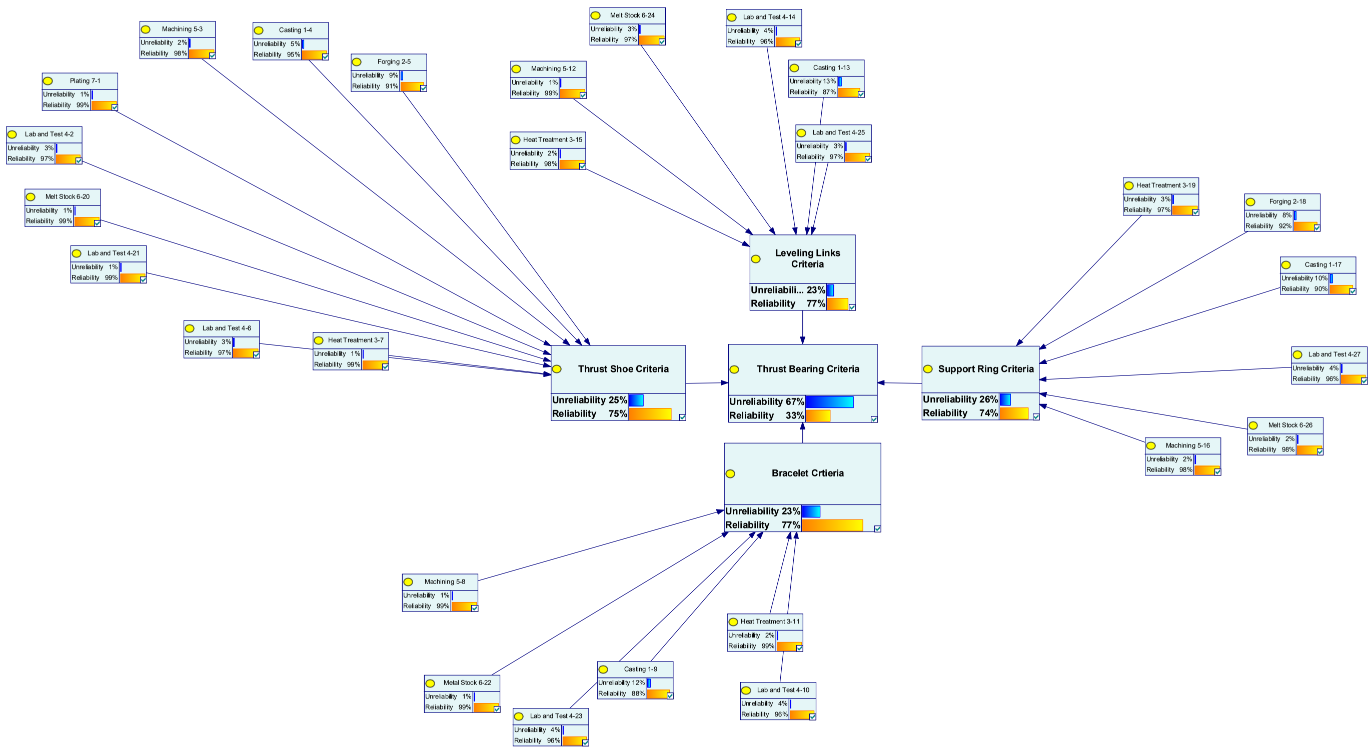


Figure A8: Updated Bayesian network that was mapped from a thrust bearing fault-tree.

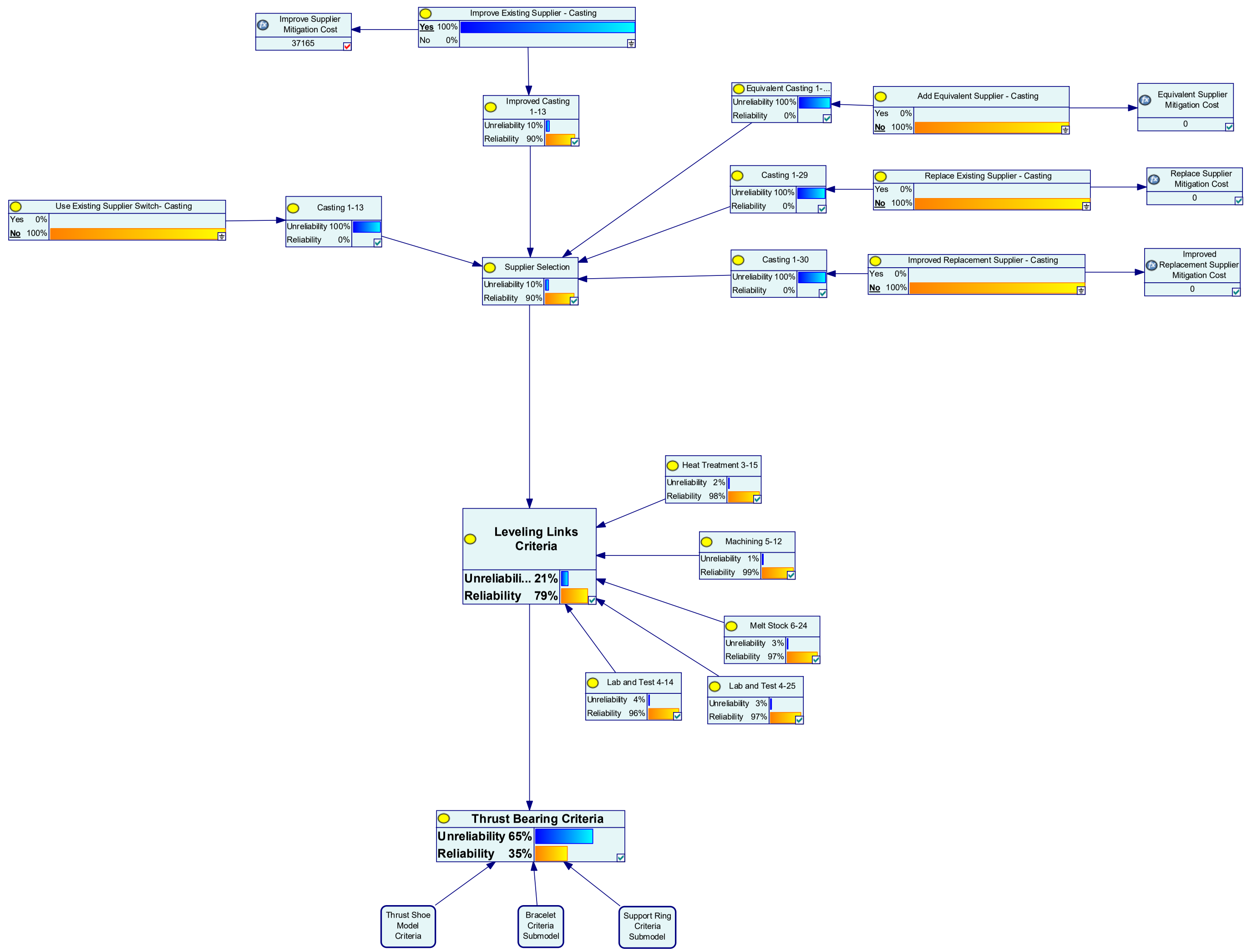


Figure A9: Bayesian network that was mapped from a thrust bearing fault-tree bill of materials with mitigation strategies that were used in [73].

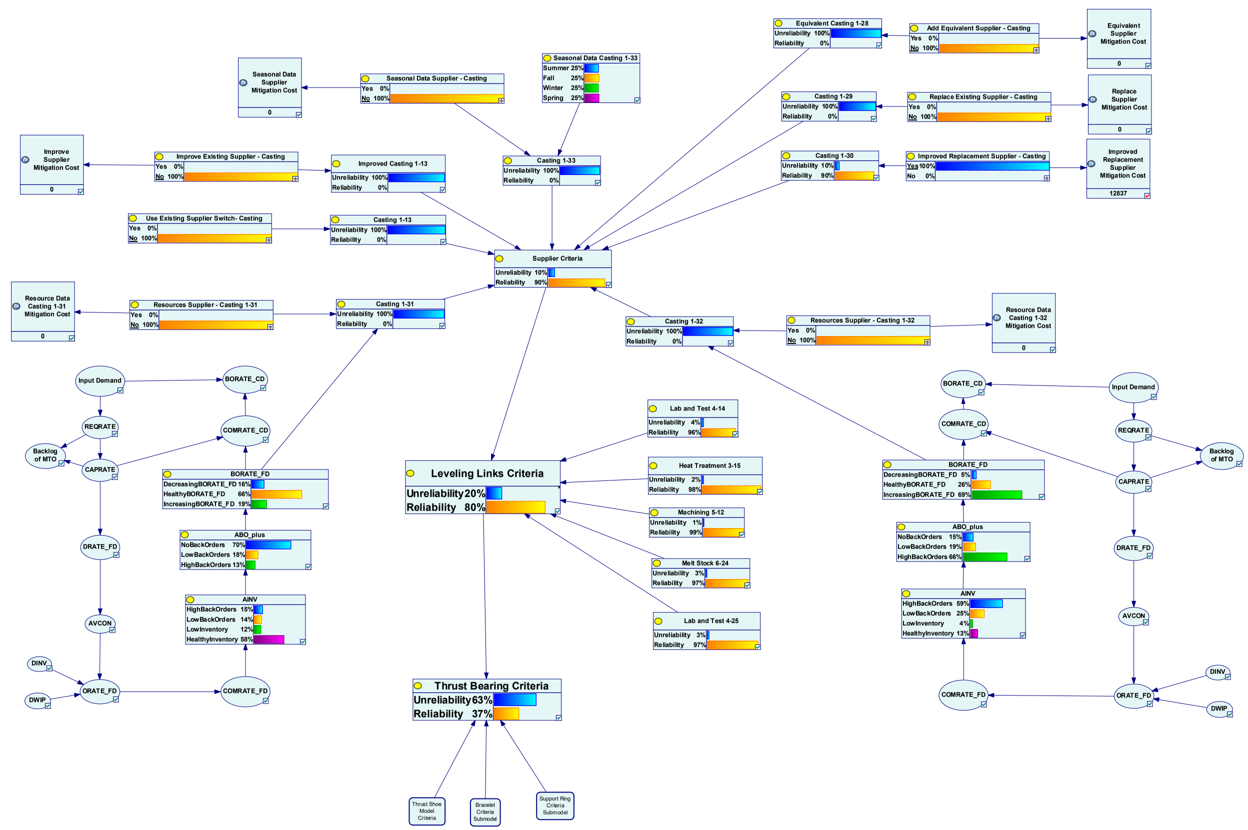


Figure A10: Bayesian network with deployed mitigation strategy of adding a new improved supplier 1-30 that has enabled inventory-production data sharing.

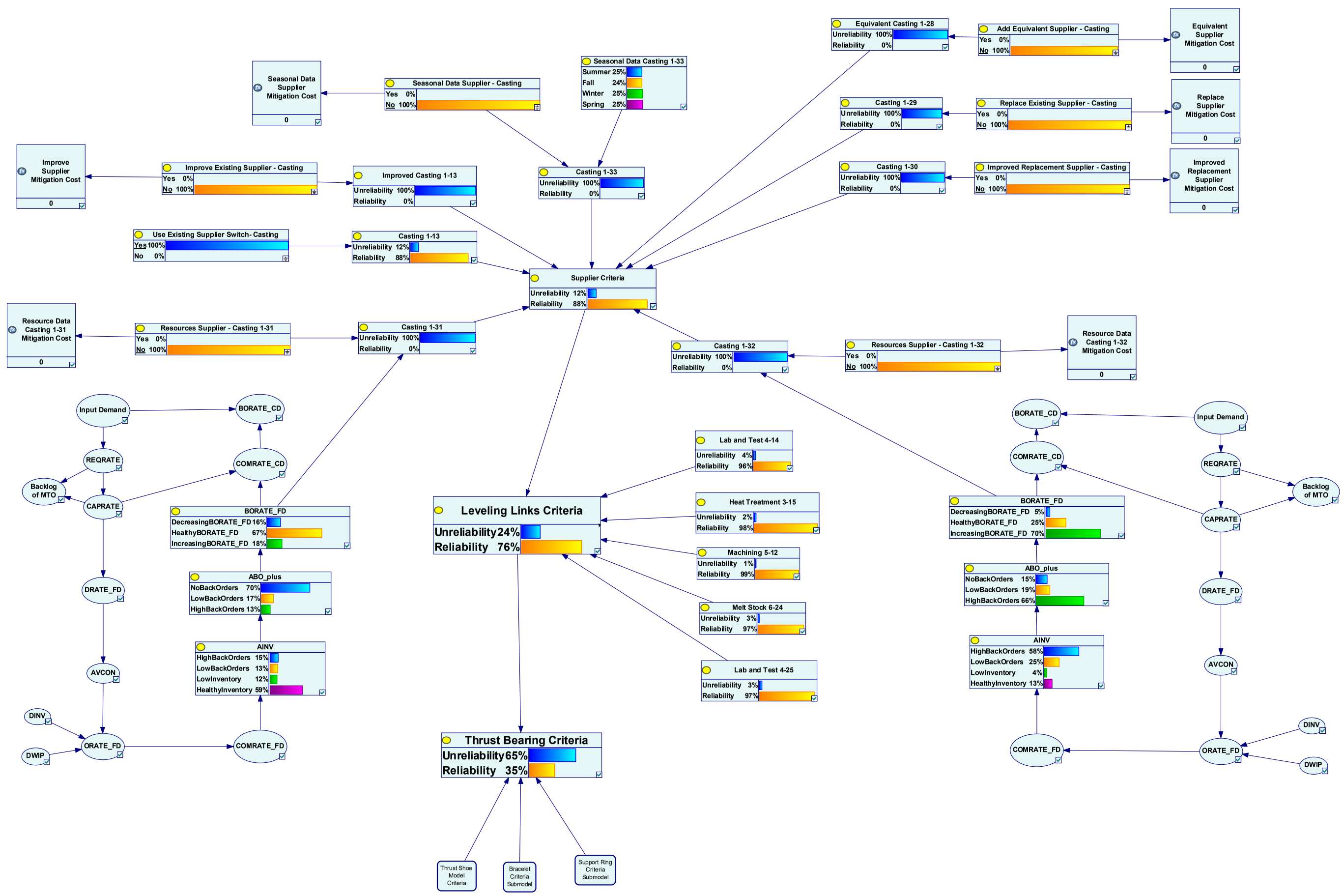


Figure A11: Bayesian network with no deployed mitigation strategies.

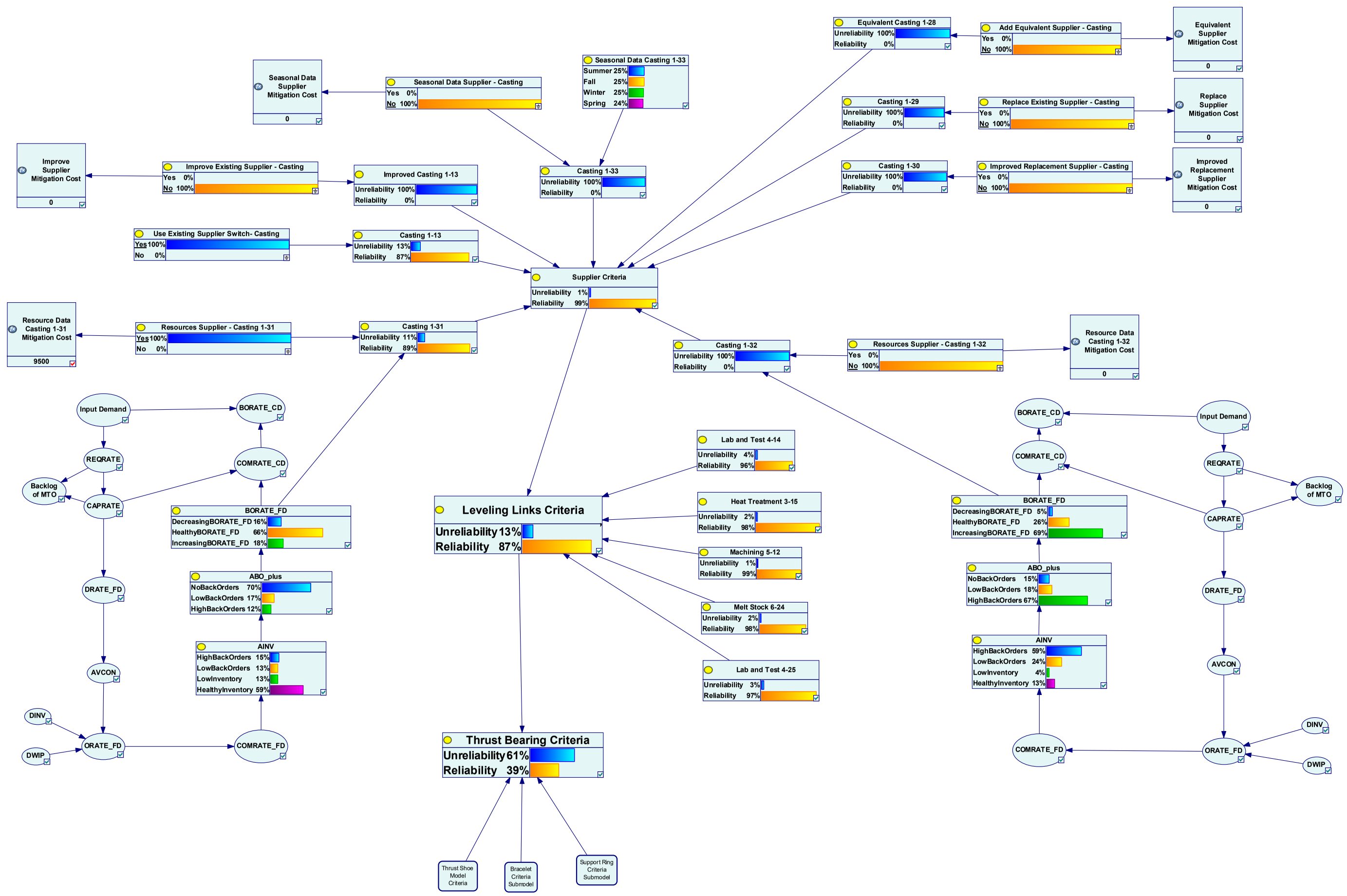


Figure A12: Bayesian network with deployed mitigation strategy of adding supplier 1-31 that has enabled inventory-production data sharing.

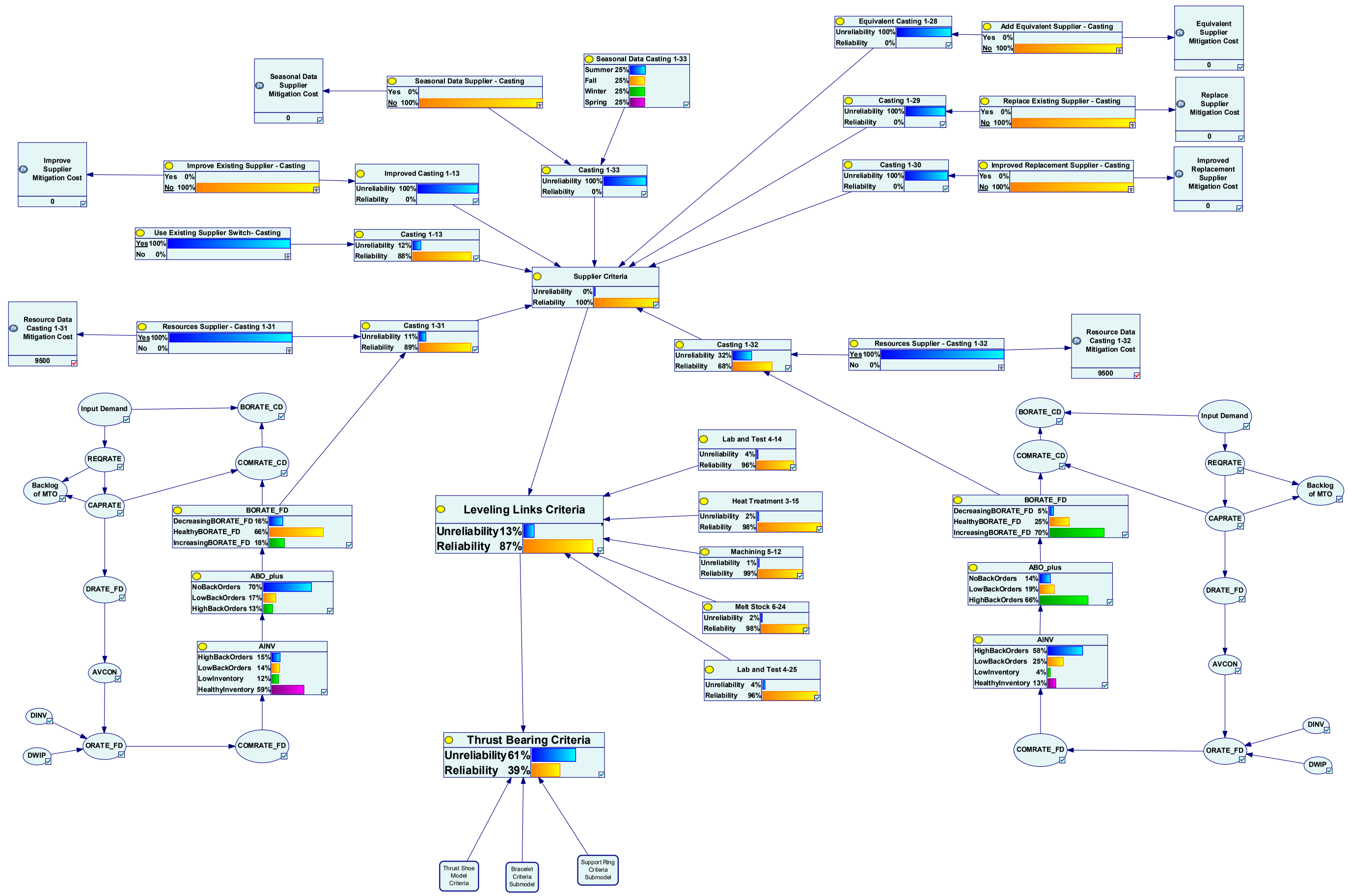


Figure A13: Bayesian network with deployed mitigation strategy of adding supplier 1-32 that has enabled inventory-production data sharing.

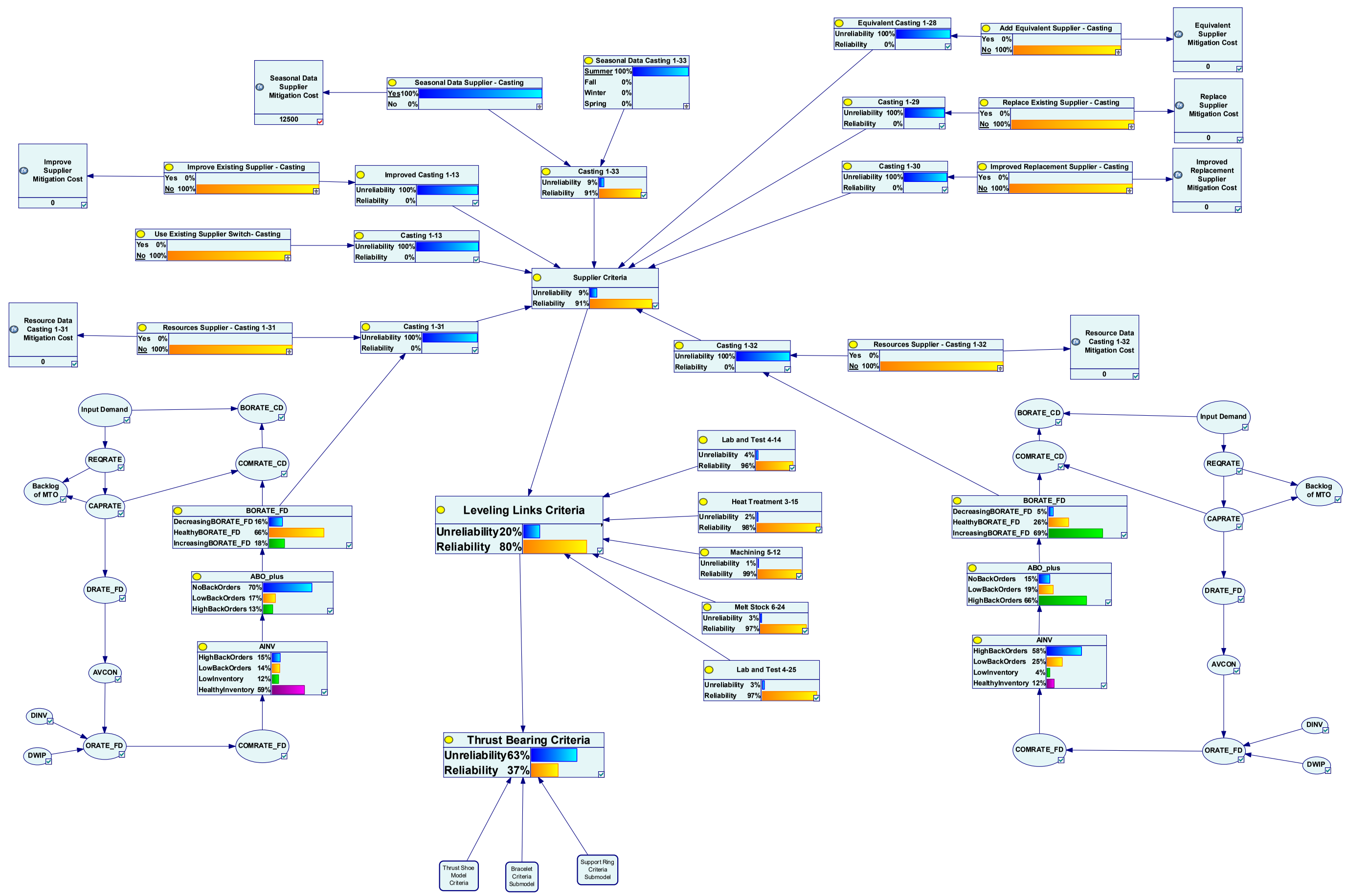


Figure A14: Bayesian network with deployed mitigation strategy of adding supplier 1-33 that has enabled seasonal data sharing with summer seasonal evidence.

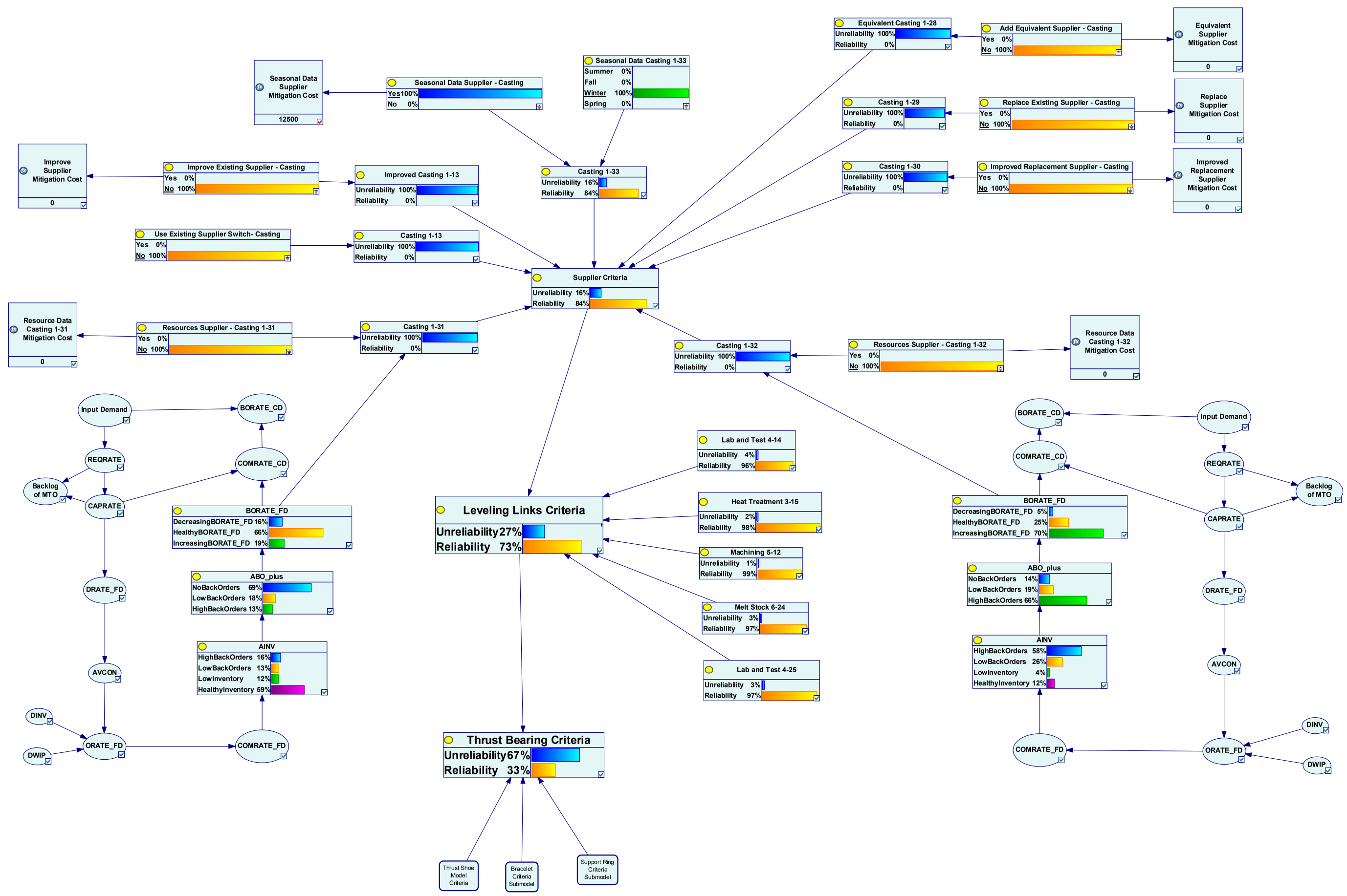


Figure A15: Bayesian network with deployed mitigation strategy of adding supplier 1-33 that has enabled seasonal data sharing with winter seasonal evidence.

Table A1: Suppliers and their unreliability to provide a thrust bearing.

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

Table A2: Difference equations for Make-to-Order/Make-to-Stock hybrid supply chain.

Make-to-Order Difference Equations
$\mathrm{REQRATE}[t] = \mathrm{DRATE}_{\mathrm{MTO}} + (1\text{-D}) \times \mathrm{BL}_{\mathrm{ADJ}}[t-1]$
$\mathrm{CAP}[t] = \mathrm{C} \times \mathrm{REQRATE}[t] + (1\text{-C}) \times \times \mathrm{CAP}[t-1]$
$\mathrm{CAPRATE}[t] = \mathrm{MIN}[\mathrm{CAP}[t], \mathrm{CAPRATE}[t], \mathrm{REQRATE}[t]$
$\mathrm{BL}[t] = \mathrm{BL}[t-1] + \mathrm{REQRATE}[t]$ - $\mathrm{CAPRATE}[t]$ - $\mathrm{BL}_{\mathrm{ADJ}}[t-1]$
$\mathrm{BL}_{\mathrm{ADJ}}[t-1] = \mathrm{BL}[t]/\mathrm{T}_{BO}$
$\mathrm{BORATE}_{\mathrm{MTS}}[t] = (\mathrm{ABO}[t]\text{-}\mathrm{ABO}[t-1])/(\mathrm{T}[t]\text{-}\mathrm{T}[t-1])$
$\mathrm{ORATE}_{\mathrm{MTO}}[t] = \mathrm{CAPRATE}[t] + \mathrm{D} \times \mathrm{BL}_{\mathrm{ADJ}}[t]$ - $\mathrm{BORATE}_{\mathrm{MTS}}[t]$
$\mathrm{COMRATE}_{\mathrm{MTO}}[t] = \mathrm{ORATE}_{\mathrm{MTO}}[t - \mathrm{T}_{\mathrm{PCD}}]$
$\mathrm{AOB}[t] = \mathrm{AOB}[t-1] + \mathrm{ORATE}_{\mathrm{MTO}}[t]$
Make-to-Stock Difference Equations
$\mathrm{DRATE}_{\mathrm{MTS}}[t] = \mathrm{CAPRATE}[t] + \mathrm{D} \times \mathrm{BL}_{\mathrm{ADJ}}[t]$
$\mathrm{AVCON}[t] = \mathrm{A} \times \mathrm{DRATE}_{\mathrm{MTS}}[t] + (1\text{-A}) \times \mathrm{AVCON}[t-1]$
$\mathrm{AINV}[t] = \mathrm{AINV}[t-1] + \mathrm{COMRATE}_{\mathrm{MTS}}[t]$ - $\mathrm{DRATE}_{\mathrm{MTS}}[t]$
$\mathrm{ABO}_{+}[t] = -\,\mathrm{MIN}(0, \mathrm{AINV}[t])$
$\mathrm{AINV}_{+}[t] = \mathrm{AINV} + \mathrm{B} \times \mathrm{ABO}_{+}[t]$
$\mathrm{DINV}[t] = \mathrm{K}_{\mathrm{INV}} \times \mathrm{AVCON}[t]$
$\mathrm{EWIP}[t] = \mathrm{DWIP}[t]$ - $\mathrm{AWIP}[t]$
$\mathrm{ORATE}_{\mathrm{MTS}}[t] = \mathrm{AVCON}[t] + \mathrm{EINV}[t-1] + \mathrm{EWIP}[t-1]$
$\mathrm{COMRATE}_{\mathrm{MTS}}[t] = \mathrm{B} \times \mathrm{ORATE}_{\mathrm{MTS}}[t] + (1\text{-B}) \times \mathrm{COMRATE}_{\mathrm{MTS}}[t-1]$

Appendix B BayesFusion

BayesFusion, LLC provides artificial intelligence modeling and machine learning software based on Bayesian networks. Their software runs on desktops, mobile devices, and in the cloud. They also offer training, scientific consulting, and custom software development. The most popular application areas of their software are diagnosis and prognosis, data science, decision modeling, and strategic planning. More information and software documentation can be found on their website (`https://www.bayesfusion.com/`) .

B.1 GeNIe

GeNIe Modeler (Graphical Network Interface) is a development environment for building graphical decision-theoretic models. It was created and developed at the Decision Systems Laboratory, University of Pittsburgh between 1995 and 2015. GeNIe Modeler provides a graphical user interface to the SMILE Engine for interactive model building and learning. Primary features include a graphical editor to create, learn, and refine network models, flexible data handling, and dynamic Bayesian networks of any order [8].

B.2 SMILE

SMILE (Structural Modeling, Inference, and Learning Engine) is a reasoning and learning/causal discovery engine for graphical models, such as Bayesian networks, influence diagrams, and structural equation models. SMILE also offers an array of programming libraries for probabilistic graphical models. SMILE is also available as wrappers to provide functionality to programs written in Java, Python, R, .NET, and COM (Excel).

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