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BAYESIAN-INTEGRATED SYSTEM DYNAMICS MODELLING FOR PRODUCTION LINE RISK ASSESSMENT

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BAYESIAN-INTEGRATED SYSTEM DYNAMICS MODELLING FOR PRODUCTION LINE RISK ASSESSMENT

THESIS

A thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in Mechanical Engineering in the
College of Engineering at the University of Kentucky

By

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2018

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ABSTRACT OF THESIS

BAYESIAN-INTEGRATED SYSTEM DYNAMICS MODELLING FOR PRODUCTION LINE RISK ASSESSMENT

Companies, across the globe are concerned with risks that impair their ability to produce quality products at a low cost and deliver them to customers on time. Risk assessment, comprising of both external and internal elements, prepares companies to identify and manage the risks affecting them. Although both external/supply chain and internal/production line risk assessments are necessary, internal risk assessment is often ignored. Internal risk assessment helps companies recognize vulnerable sections of production operations and provide opportunities for risk mitigation.

In this research, a novel production line risk assessment methodology is proposed. Traditional simulation techniques fail to capture the complex relationship amongst risk events and the dynamic interaction between risks affecting a production line. Bayesian-integrated System Dynamics modelling can help resolve this limitation. Bayesian Belief Networks (BBN) effectively capture risk relationships and their likelihoods. Integrating BBN with System Dynamics (SD) for modelling production lines help capture the impact of risk events on a production line as well as the dynamic interaction between those risks and production line variables. The proposed methodology is applied to an industrial case study for validation and to discern research and practical implications.

KEYWORDS: Risk assessment, production line, Bayesian Belief Networks and System Dynamics.

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1. Introduction

1.1 Background

Risks are unavoidable due to the complex and dynamic nature of operations. Risks have the potential to alter a company's performance in a devastating manner. As a result, organizations are seeking methods that would help identify and manage these risks. This has led to an increased realization of the importance of risk management and the benefits of undertaking such initiatives. The Institute of Risk Management (IRM, 2002) states that "risk management marshals the understanding of risks effecting the organisation, increases probability of success and reduces uncertainty regarding company's ability to achieve set targets."

ISO 31000 (2015) defines 'risk' as "the effect of uncertainty on objectives." It further defines 'effect' as "deviation from the expected" and 'uncertainty' as "the state of deficiency of information related to an event." Risk is expressed in terms of the likelihood of occurrence and the consequence of the risk event.

ISO 31000 (2015) further defines risk management as "the performance of coordinated activities to direct and control an organization with regard to risk. Risk management practices are aimed at identifying, assessing and mitigating risks impacting an organization." ISO 31000 (2015) has streamlined the risk management structure by providing some guidelines which is summarized in Figure 1. As shown, establishing the context, risk identification, risk analysis, risk evaluation and risk treatment are the five key steps in the process. Concurrently, communication, monitoring and reviewing are additional tasks that enhances the effectiveness of each step in the risk management process.

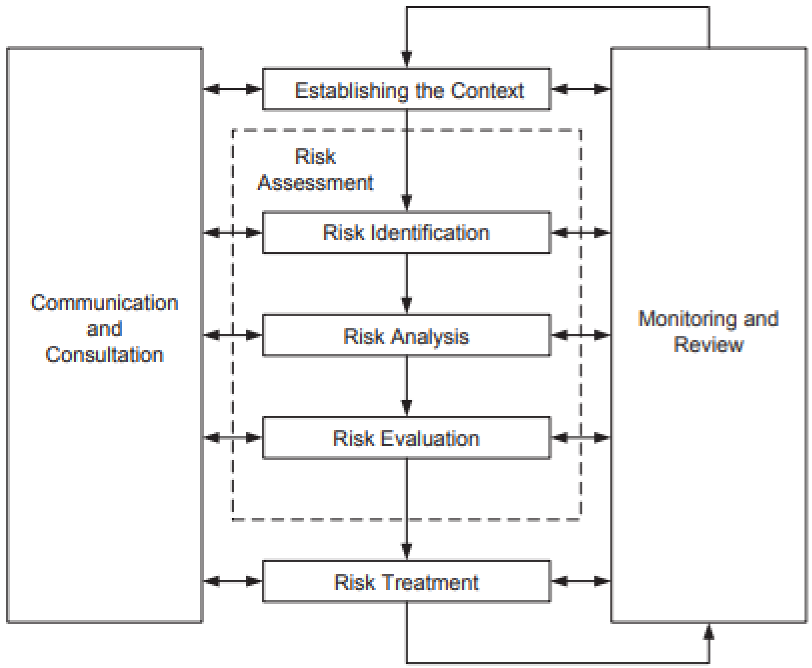


Figure 1: ISO 31000 risk management framework (2015)

1.2 The Current Status

Increased complexity in products to be manufactured, strict regulations and a continuously changing market have led to an increase in risks affecting the manufacturing sector. Succeeding in such competitive markets may require adopting bold strategies. Often, production capacities and capabilities are quoted aggressively in order to secure more customers. Under such circumstances, the failure to respond quickly to raw material shortages, downtimes, deteriorating equipment conditions, or other operational risks could have expensive consequences. Company-wide risk assessment can provide a more holistic view of the risks affecting a company and better opportunities to mitigate them. The scope of a company-wide risk assessment must include both internal and external operations. External/supplier risk assessment has drawn significant attention compared to internal/production line risk assessment. William et al., (2015) identified this trend when only three studies on manufacturing/internal risk assessment were found compared to several in the field of supply risk assessment. Even though the scope of risk assessment is much narrower with internal operations, adopting comprehensive internal risk management practices can be of significant importance as it can enable a company gain competitive advantage over its competitors by ensuring financial strength, quality of goods and services, and increased customer satisfaction.

Companies suffer from significant losses and diverge from their business plans when risk events occur. Hence, they are always seeking for ways to assess the impact of various risks and respond to them. External risks are extremely complex in nature and have a large impact. Controlling or mitigating external risks is a tedious task and usually requires the effort of multiple individuals. On the contrary, internal risks are comparatively less complicated and their management often within the scope of the supervisor or engineer. However, the use of structured methods for internal risk management is overlooked in many companies. Using well-defined methods for internal risk assessment can offer high returns with minimal resource expenditure and bring reliability to the production line. Nevertheless, as pointed out by William et al., (2015), very few studies have focussed on developing better methods for internal risk assessment. Amongst the various internal aspects susceptible to risks, production operations (lines) are one of the most critical areas that need attention. Hence, the focus of this study is on risk assessment at the production line level.

Current techniques of risk assessment are not sufficiently comprehensive to assess internal risks. Most techniques do not provide enough information to the industry personnel to solve the problem effectively. Popular techniques such as using a risk matrix approach can help visualize risks impacting the production line but fail to capture the relationship between risks. Techniques like Fault Trees, Event Trees and Bayesian Belief Networks (BBN) help capture the inter-relationships amongst risk events and quantify risk likelihood but fail to account for the impact of these risk events on the production line, making them one directional. Alternatively, simulation techniques like System Dynamics (SD) can enable users to envision the impact of risks on the production line and the dynamic interaction between risk events through feedback loops. However, SD fails to effectively capture relationships amongst risk events and calculate conditional risk likelihoods. Risk assessment should be conducted to understand both the likelihood and potential impact of risk events on production line. Failure to understand both these aspects of risks, defeats the whole purpose of conducting risk assessments.

1.3 Research Objective

Therefore, the objectives of this thesis research are to:

1. Develop a methodology to evaluate production line risk, which can capture the dynamic nature of risk events and their relationships with each other.
2. Assess the impact on the production line, upon exposure to risk events, over a period to evaluate the effectiveness of the method developed.

The remainder of the thesis is organized as follows. Chapter 2 presents a literature review where the current methods of risk assessment are presented and research gaps are identified. Since studies on risk assessment at the production line level is not extensive, supply chain risk assessment methodologies (which can also be used for assessing risk at production line level) have also been considered. The methodology developed for risk assessment at the production line level is presented in Chapter 3, taking into consideration the research gap and the objectives. The application of methodology to a production line case study is presented in the following chapter. The results obtained from the model are described in Chapter 4. Further, the effectiveness of the methodology in assessing the behavior of the production line system is also examined. Conclusion about the research work and the degree of success with which the research objectives were achieved are described in the following chapter. A discussion of future work, based on the limitations of the model, is also presented in this section.

2. Literature Review

ISO 31000 (2015) defines risk assessment as a three step process: risk identification, risk analysis and risk evaluation. The literature related to each of these areas, particularly in relation to production line risk assessment, is presented individually in the following sections.

2.1 Risk Identification

At the production line level, Risk identification involves the process of recognizing the risks impacting the production line and recording them. IRM (2002) recommends a comprehensive understanding of the organisation's activities, internal and external, in order to identify risks impacting the organisation and having a detailed description of these risks presented in a tabular form to facilitate risk assessment. It lists out several risk identification techniques such as brainstorming, questionnaires, incident investigation, auditing and inspection, Hazard and Operability Studies (HAZOP) etc. Along with these traditional techniques, risk taxonomies can prove to be an effective guide during the risk identification phase. Rao and Goldsby (2009) identified the risks impacting supply chains where risks were broadly classified as environmental risks, industry risks and organisational risks. In addition, Badurdeen et al., (2014) presented a comprehensive supply chain risk taxonomy.

Amongst these noted techniques, HAZOP is one of the most structured methods for risk identification at the production line level. HAZOP has been widely used in the oil and chemical process industries in identifying process related risks as pointed by Bustad and Bayer (2013). HAZOP is a technique where events causing deviations in the process are identified, making use of process flow diagrams and process parameters information.

Users go through all the technical details of the process to break it down into several sections. These sections are then studied in detail to identify possible deviations in the process and their potential causes. Arief et al., (2009) advocates the use of HAZOP based methodology to identify risks impacting supply chain. They call for a careful assessment of the process, through a process flow diagram, to search for deviations using a set of guidewords in combination with system parameters for identifying risks in the supply chain. Amongst the many aspects of supply chain that the paper deals with, operational department is what is applicable at the production line level. Despite HAZOP being a well-structured method for identifying risks, the extent of information required on the process is discouraging. One of the pre-requisites for using HAZOP is that the process must be well defined with a set of parameters for each operation. Quality of risk identification process through HAZOP is heavily dependent on the availability of these process details. Bustad and Bayer (2013) also argued about the limitations of HAZOP in identifying unforeseen risks. In addition, the method is highly time consuming and therefore expensive. Alternatives like brainstorming and auditing were also explored. Independent and dependent risk events can be identified well using these alternatives. Furthermore, Bustad and Bayer (2013) support the idea of combining some of these techniques to make risk identification process more reliable.

However, brainstorming and auditing at the production line level need direction and defined boundaries as it is easy to digress from the line level. The subjective nature of these methods make it difficult to identify risks in a systematic manner. A good way to overcome this limitation is to adopt a value based thinking. Shah et al., (2013) identify risks at the line level based on its impact on the ability of process to deliver the value proposition.

Identifying risks having an impact on value proposition helps streamline the process of risk identification at the line level by providing direction and filtering out the unnecessary risks. The organisational risks cluster from Rao and Goldsby (2009) and the operating risks sub-cluster in Badurdeen et al., (2014) can be useful in identifying risks relevant at the production line level. Risk events like raw material shortages, process changes and machine failure are widely applicable. These risks, listed in the risk taxonomy, may or may not impact a specific production line but they serve as a guide during risk identification phase.

2.2 Risk Analysis

Risk analysis is the process of examining the risk impacting the production line. Since production line risk assessment is a less explored field, published literature in supply chain risk assessment was reviewed extensively. Quantitative risk assessment was the prime focus of the review.

Risk matrix is the most commonly used approach for risk analysis in risk management studies as pointed out by Peace (2017). A risk matrix consists of two variables, risk likelihood and severity. The risk matrix is further categorized into high, medium and low risk zones. This provides the user with the visual evidence of the nature of risk and the priority with which the risk events need to be addressed. This approach was developed at US Airforce Electronic Systems Center by Paul et al., (1995) to assess risks on one of their applications. The risk matrix has been applied in several other risk management studies including project management (Murray et al., 2011), supply chain management (Bustad and Bayer, 2009, Li et al., 2013, Kodithuwakku, 2015) and in maintenance suppliers' management by Antosz et al., (2017). Bustad and Bayer (2009) presented a risk management process at Coca Cola Enterprises by combining HAZOP and risk matrix methods. They identified supply chain risks impacting the industry through HAZOP and assessed them using a risk matrix. This approach is good for creating awareness and could work as a quick overview of the risks impacting the production line. However, the risk matrix method is mostly qualitative. One major flaw of this method is that it fails to prioritize risk events with low probability but a very high impact (natural disasters, terrorist attacks etc.) as the overall risk value would be low. Also, they are not capable of accounting for the uncertainty in complex systems.

Using Fault Trees are another popular approach for risk analysis in risk management studies. Fault trees are based on the fundamental principle of converting physical systems into logical expressions where a set of causes lead to an event of interest. The application of fault trees in assessing the reliability of a production line was demonstrated in Zhang et al., (2011) and Ariavie et al., (2012) and for inventory risk assessment within the aerospace industry in Chen-Yang et al., (2013). This approach gives an insight into the events resulting in a failure event. However, its dependence on logical operators thwarts it from being able to capture the complex inter-relationships amongst risk events. Also, the deterministic nature of fault trees fail to capture the stochastic nature of models/systems.

Event Trees are also used for risk analysis in risk management studies. Event trees are used to model the consequences occurring from an initiating event based on Boolean logic. Moshen and Keren (2011) demonstrate the use of event trees in assessing reliability of safety systems. They were able to calculate the probabilities of risk events and identify the major sources of safety system failure. As risk events identified in the safety system were few in number, event trees were able to evaluate risk likelihood effectively. While event trees help identify failure propagation across the system, they are not effective to evaluate risk in complex systems due to their dependence on Boolean logic and deterministic nature.

Bow-tie modelling is another technique used to combine the benefits of using fault trees and event trees. Left side of the bow-tie consists of a fault tree which models a set of events resulting in the occurrence of the identified event. This event branches out to form event trees and thus model the consequence of that event. BT has been applied in risk management studies within manufacturing sector by Pereira et al., (2015) and Pereira and Lima, (2015) and in safety analysis of process systems by Khakzad et al., (2013).

Bayesian Belief Networks (BBN) is an effective tool to capture both the interdependencies between risk events and uncertainty in likelihood. Unlike fault trees and event trees, BBN make use of Node Probability Tables (NPT) to represent the conditional probabilities between parent and child risks. BBNs are a probabilistic approach, based on Bayes theorem, used for decision making under uncertainty (details are included in chapter 3). BBN models have been used as a risk assessment tool in various fields: fault diagnosis in a hydropower plant using BBN was discussed by Chaur and Sou (2013); supply chain risk analysis using BBN was demonstrated by Badurdeen et al., (2014) and additional case studies were presented in Amundson et al., (2013); supply network risk propagation by Garvey et al., (2015); information risk in supply chain by Sharma and Routroy (2016) and ecological risk assessment in ecosystems was discussed by McDonald et al., (2015). Garvey et al., (2015) capture the interdependencies between risk events by constructing a BBN model. The research quantifies risks occurring at various nodes and captures their propagation across the supply chain. The usage of BBN to capture risk propagation across the supply chain is a valuable learning point. Sharma and Routroy (2016) assess information risk factors like information security, information leakages and reluctance towards information sharing on the supply chain. They highlighted BBNs capability in handling subjective data along with objective data. Badurdeen et al., (2014) outlined a well-structured method for supply chain risk assessment by linking the risk drivers to the performance measures. This model captures the uncertainty within the system in an effective way. However, the risk events analyzed are static in nature. In reality, risk events evolve with time and dynamically interact with the system. Also, they fail to capture the impact of risk events on the system. Thus, BBN models alone may not be enough for risk analysis.

Dynamic causal relations can be modelled well using simulation tools such as System Dynamics (SD). SD is a powerful tool comprising of stocks and flows. Stocks represent levels, which can be used to represent inventories, cash reserves, etc. Flows determine the quantity of stock that is moving from one location to another. A simulation of a model of a system demonstrates the change in stocks and flows over a period. The SD approach has been applied in the field of risk assessment. Risk analysis using SD on a new product development process was demonstrated by Dehghanbaghi and Mehrjerdi (2013) to study the impact of risk events on performance metrics like sales, production, government support and raw materials. They quantified risks by multiplying risk likelihood and severity. The model was then simulated to assess the impact of risk events on the metrics mentioned above. Although they were able to capture the impact of risk events on system variables, multiplying risk likelihood and severity might be misleading as pointed by

Bustad and Bayer (2009). They argued that multiplying risk factors fail to capture risk events with low likelihood and high severity or vice-versa. Similarly, the risks associated with NASA's shuttle launching system was studied by Dulac et al., (2005) using SD to capture the dynamic nature of risks and their impact on the shuttle launch.

SD models could capture the impact of risk events on the system; however, SD models have difficulty in representing relationships between risk events due to their subjective nature. Therefore, combining SD and BBN can prove to be an effective way to capture both the probabilistic exposure to risk events and the transient impact over time. Mohaghegh (2010) demonstrated the combination of SD and BBN for Socio-Technical Risk analysis. The author modelled risks using a BBN software and connected it with SD simulation model. The model is capable of capturing dynamic nature of variables within the system through SD and BBN captures inter-relationships and uncertainty in risk events. A major limitation of this approach is in simulating the data. For each time step, data had to be transferred between the two softwares. This severely limits the number of time steps for which the data can be simulated.

While production line risk assessment has been addressed before, most of the methods used provide only a limited perspective, often using qualitative and deterministic information. Integrating capabilities offered by different tools can provide a more versatile approach to evaluate risks at the production line level.

Alternatively, the P-graph methodology was explored in dealing with risk management. Varga et al., (2010) describes P-graphs (process graphs) as bipartite graphs, consisting of nodes for a set of materials, a set of operating units, and arcs linking them.

The set of materials can be the raw materials, intermediate products/materials, or products. The operating units are defined in terms of input and output materials as well as their ratios. P-graphs have been used in optimizing supply chain under uncertainty by Sule et al., (2011) and increasing reliability in bio-diesel supply chains by Bertok et al., (2013). P-graphs can be used to model a production line by using material nodes for raw materials, work in process inventory and finished goods. Operating units can be used to model the workstations through which the material flows. However, its limitation in representing complex relationships between risk events and its inability to capture stochasticity in process parameters make it a less preferred option.

Additionally, mathematical programming models were explored for their suitability for assessing risk. Kungwalsong (2013) developed a multi-criteria optimization model for supply chain disruption risk management. To handle multiple and conflicting objectives, goal programming was used. Disruption risks were quantified based on hazard, vulnerability and availability of risk management practices. This risk was used as one of the factors in the optimization model. The author was capable of providing the tradeoff between multiple objectives such as profit, risk level etc. Medina-Herrera et al., (2014) developed a mixed-integer non-linear programming model for optimal plant layout. Plant safety risk was considered as one of the parameters for optimizing plant layout. The model was able to optimize the layout based on multiple factors like distance, profit and risk levels. Mathematical programming models are suitable for constructing selection models by considering risk factors. However, they fail to capture the inter-dependencies amongst risk events in a complex system.

Risk analysis at the production line level requires the method adopted to be capable of handling a complex system with inter-dependent variables. Amongst the techniques discussed, fault trees, event trees and BBN are most suitable at the production line. Their ability to capture relationship between risk events helps calculate risk likelihood. However, they fail to capture the impact of risk events on the production line and the dynamic interaction between risk events and the production line. Alternatively, SD is extremely relevant at the production line level. SD is capable of depicting the production line and assess the impact of risk events over a simulation time period. Its feedback-loop property helps in capturing the dynamic interactions between risk events and production line variables. However, it fails at calculating risk likelihood in an effective way. Perhaps, integration of two or more methods might provide a better a way to quantify both the risk likelihood and the impact of risks on production line.

2.3 Risk Evaluation and Risk Treatment

Risk evaluation is the process of prioritizing risks for risk treatment. Risks analyzed are compared against the standards or preferred criteria to determine the priority. These prioritized risks are then treated.

Risk treatment is the process of developing strategies to treat risks. ISO 31000 (2009) provides several options for risk treatment:

(1) avoiding the risk by deciding not to start or continue with the activity that gives rise to the risk;

(2) taking or increasing the risk in order to pursue an opportunity;

(3) removing the risk source;

(4) changing the likelihood;

(5) changing the consequences;

(6) sharing the risk with another party or parties;

(7) retaining the risk by informed decision.

Bilsel (2009) developed a multi-objective mathematical model solved using goal programming approach to develop risk mitigation strategies. The model assigns primary suppliers and backup suppliers to the buyer and determines order quantities. By assigning backup suppliers, supply risk is mitigated. Scenario analysis is another approach to evaluate risk. Miller and Waller (2003) describe scenario analysis as "a way of structured thinking in which stories are created that bring together factual data and human insight to create scenarios exploring future possibilities." Miller and Waller (2003) and Daszyńska-Żygadło (2012) advocate the use of scenario analysis in risk management studies. Miller and Waller (2003) analyzed scenarios at a corporate level across a firm's portfolio of businesses. Their study empowered managers to make investment decisions under uncertainty. Daszyńska-Żygadło (2012) used the method to understand the exogenous risks influencing the operations of a company. This research was aimed at improving organizational learning and its ability to develop responses to react and recover form occurrence of risk events. Analyzing the system under several scenarios aids its users in decision-making under uncertainty.

The literature review systematically reviews the current techniques used for the three aspects of risk assessment: risk identification, risk analysis and risk evaluation. This helped understand the merits and demerits of the current techniques and identify research gaps.

Brainstorming and auditing are effective at identifying risks at the production line level. Adopting a value based thinking, when using these methods, prevents from digressing from the scope. Additionally, risk taxonomies serve as a guide during risk identification phase. When abundance of data and time is available, HAZOP is a good technique to explore.

Risk analysis at the production line level requires the technique to quantify risk likelihood, influenced by several interdependent risks, and the dynamic interaction between risk events and production line variables. Risk matrix is a simplistic approach to analyze risks but fails at the production level due to the intricacies in the system. Fault trees, event trees, bow-ties and BBN are effective at quantifying risk likelihood. BBN, especially, is extremely relevant at production line level due to its capability of calculating risk events' likelihoods in a complex interdependent system. It uses causal relationships between risk events to determine their likelihood. However, they fail to capture the dynamic interaction between risk events and production line variables. Alternatively, SD simulation technique could assess the impact of risk events on the production line and capture the dynamic nature of system variables. However, unlike BBN, they fail to capture the interdependent risks in the system. The P-graph technique could be used to depict the production line model and can analyze the propagation of risks through the system. However, their deterministic nature restricts their use in being used as a simulation model. Also, interdependencies between risk events cannot be captured through this technique. Mathematical models don't have much relevance at the production line level as the intricate details of production line are required to be converted into a mathematical programming model. None of the above mentioned techniques for risk analysis are capable of analyzing both the risk likelihood and the impact on the production line. A new technique or an integration of techniques is required to analyze risks at the production line level effectively.

Risk evaluation using scenario analysis approach enables users to evaluate risks impacting the production line and develop strategies for risk management. Several simulation techniques have the inbuilt feature of scenario analysis. Using SD simulation would allow to assess the impact of risk events on the production line and to test several scenarios. Results from this would aid users in decision making when a risk event occurs.

3. Research Methodology

A production line risk assessment framework that is developed in this research is depicted in Figure 2. A risk taxonomy relevant at the production line level is developed during the risk identification phase using brainstorming and referring to general risk taxonomies. Risk identification is followed by risk analysis. Most techniques for risk analysis fail to capture the dynamic and interdependent nature of risk events and their impact on the production line. In this research, a combination of BBN and SD is chosen to develop a more versatile technique for risk analysis (details are included in section 3.2). Lastly, risk is evaluated through scenario analysis. Each of the steps shown is described in detail in the following sections.

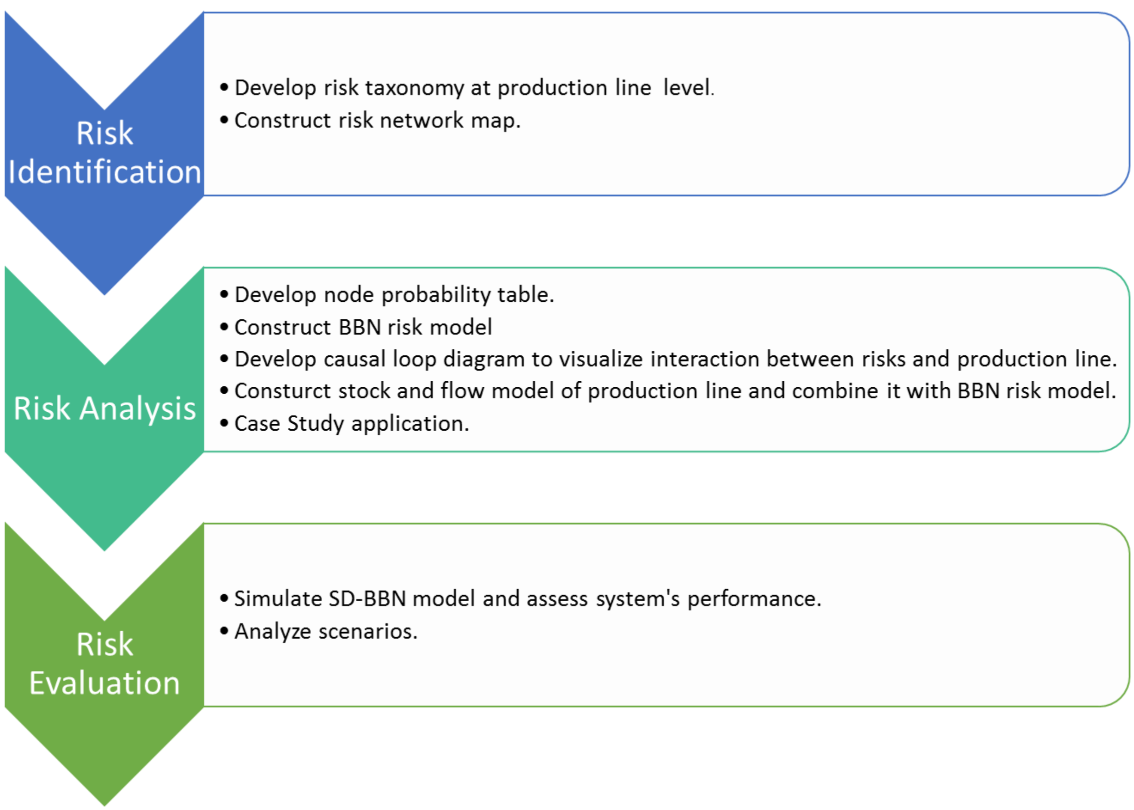


Figure 2: Production Line Risk Assessment Framework.

3.1. Phase I: Risk Identification

Risk identification is the most crucial step for risk assessment. Identifying potential risks relevant at the production line level establishes a strong foundation for the subsequent stages of risk analysis and risk evaluation. One of the most challenging tasks during this phase is to define the boundaries within which risk would be assessed, as it is very easy to digress from production line level risks to organizational /industry level risks. The best way of defining these boundaries is to have a discussion with the team assessing risk and come to a consensus on the scope of risk assessment.

To support the process of risk identification, the risk taxonomy developed by Badurdeen et al., (2014) was used as a starting point. The operational risks are listed in Table 1. These risks were utilized as a guide during risk identification phase. Such a guide allows in selecting risks relevant to the case-study or the scope of risk assessment.

Table 1: Operational risks from Badurdeen et al., (2014)

Subcategory	Risk dimensions
Organizational Operating	Raw material shortage.
	Quality variability
	Employee productivity due to labor unrest/strikes
	Machine failure
	Spare part restriction
	Work/life unbalance, unsocial hours of working
	Technology – outdated hardware (inability to adapt new technologies
	Inventory management problems
	Increased costs of disposal to landfills
	Nature of regulations faced (OSHA, EPA) – hazardous materials used in the factory
	Poor traceability – high costs to trace
	Communication/IT systems (hardware, software, hackers, virus, worms)
	Process changes, machine changes/upgrades

Apart from these risks listed in the risk taxonomy, there are other potential risks that can be unique to an organization or an industry. These risks are identified through some conventional techniques like brainstorming, surveys and audits. Alternatively, a detailed approach of HAZOP could be used when abundant data regarding the process is available.

Merely identifying individual risks impacting the production line is of little value if the inter-relationships between these risk events aren't understood. Often, the occurrence of one risk event effects the occurrence of a dependent risk event. Badurdeen et al., (2014) demonstrated the importance of capturing the causal relationships between risk events to analyse the propagating effects of risk events. Developing a risk network map is an effective way to visualize the inter-relationships between the risks effecting production line. A risk network map is a qualitative technique of representing the causal relationship between various risk events and production line KPIs.

Additionally, for an effective risk assessment, both the risk events and their impact on the production line need to be taken into consideration. The impact of these risk events on the production line is assessed by evaluating the impact on selected Key Performance Indicators (KPIs).

3.2. Phase II: Risk Analysis

The approach followed to analyze risk at the production line level is depicted in Figure 3. Quantifying risks requires a risk assessment model capable of handling both objective and subjective risks, capturing inter-dependencies and having a strong mathematical foundation to calculate likelihood of risk events.

Assessing risks over a period of time required studying the system for transient behavior. System dynamics (SD) is chosen as the technique to simulate behavior as it allows user to observe the behavior of the production line and test its performance under different scenarios. Simulation techniques such as SD, alone cannot capture sudden changes/disruptions in production line caused by risk events. This limitation can be overcome by combining simulation with risk assessment techniques. Bayesian Belief Networks (BBN) was found as an effective method to capture the conditional probabilistic relationship between risk events. Thus SD, when combined with BBN, can provide a versatile technique to assess the production line under the influence of risk events

Additionally, a suitable platform is required to model the production line, capture the interaction between production line simulated and BBN risk model used to model the conditional relationships and dynamic nature of risk events (via a feedback mechanism from the line to the BBN risk model).

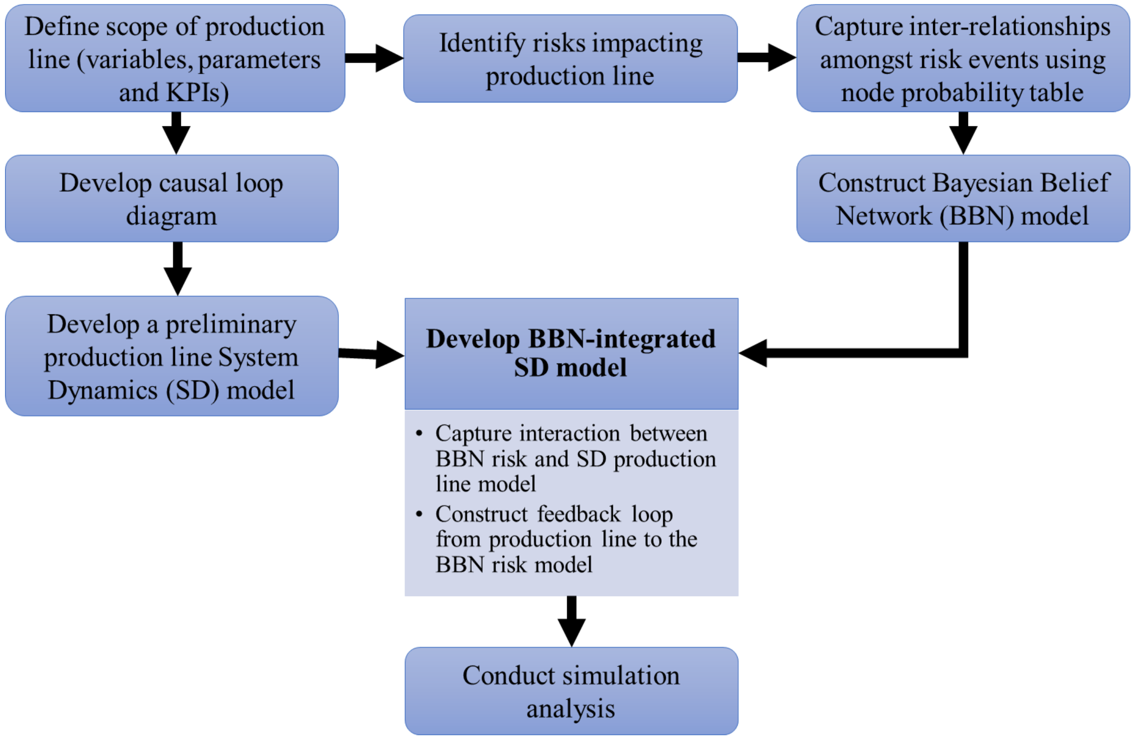


Figure 3: Risk Analysis Approach.

3.2.1. Bayesian Belief Networks (BBN)

BBNs are a robust probabilistic approach often used for reasoning, diagnosis, prediction and decision making under uncertainty. Pai et al., (2003), Cowell et al., (2007) and Lockamy and McCormack (2012) recommend BBN as a tool that allows users to model subjective beliefs with available evidence. Their ability to exploit quantitative and qualitative data to generate posterior probabilities is of help in the field of risk assessment. Pearl (1985) defines BBNs as directed acyclic graph, which consists of nodes and arcs connecting dependent nodes. Nodes represent variables like product quality, supplier issues etc. Fenton and Neil (2012) provide a deep insight into BBN modelling. The different types of nodes mentioned by Fenton and Neil (2012) are:

(a) Ranked nodes: Ranked nodes are discrete variables whose states are represented on a scale from 0 to 1. Each state has an interval width and label associated with it. Ranked nodes are extremely useful in representing variables having different states. For example, quality of work, level of experience, chance of snowfall, etc., are well expressed using ranked nodes. Each ranked node has a predetermined number of states and interval width associated with it. Consider a ranked node known as quality of work with 5 possible states (poor, below average, average, above average and excellent) and the interval width being 0.2 as shown in Table 2. Thus, quality of work is poor when the value is between 0-0.2, below average when the value is between 0.2-0.4 etc.

Table 2: Ranked Nodes - BBN

State	**Interval**
Poor	0-0.2
Below average	0.2-0.4
Average	0.4-0.6
Above average	0.6-0.8
Excellent	0.8-1

There are several real life cases where nodes can be represented suitably as a state but not as a discrete number between 0-1. One such example is illustrated below in Figure 4. The skill of operator, dedication of operator and quality of work are nodes measured on a subjective scale (poor, below average, average, above average, excellent).

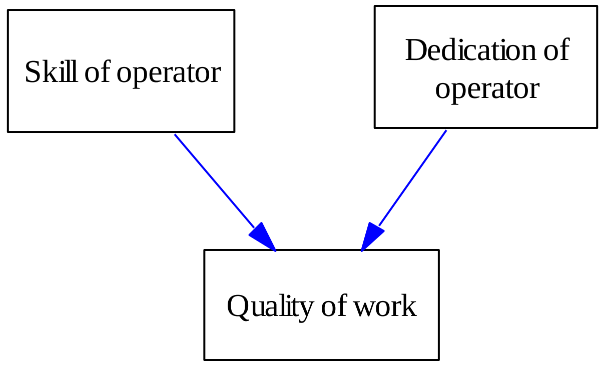


Figure 4: BBN ranked nodes example.

Considering skill of operator, dedication of operator and quality of work consists of 5 states, a weighted function is used to determine the state of child node (quality of work) depending on the parent nodes.

(b) Boolean nodes: Boolean nodes are used to define nodes with only two states, True (1) and False (0). There are several real life cases where only 2 states are possible, for example, Medical test (positive and negative), Marriage (yes and no) etc. Contrary to ranked nodes where weighted functions are used to determine the state of child node, Boolean nodes make use of logic operators to determine the state of the child node. Several logic operators can be used in BBNs.

OR operator: OR operator is used in cases where the child node C is true when parent nodes A or B are true. An example is shown below in Figure 5. Child node "bad weather" is true when parent nodes "rainfall" or "snowfall" is true.

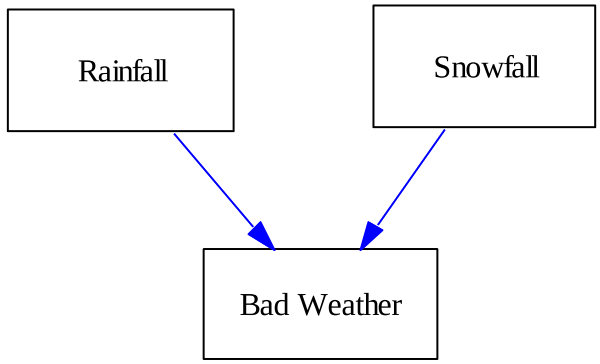


Figure 5: OR operator example.

AND operator: AND operator is used in cases where the child node C is true when both parent nodes A and B are true/false. For example in Figure 6, a power failure can only occur when both the main power supply and the backup power supply fail.

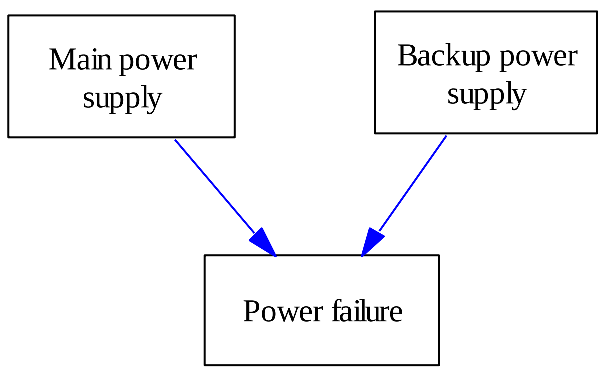


Figure 6: AND operator example.

M from N operator: The M from N operator is used in cases where the child node C is true when M out of N (M<=N) parent nodes are true. For example in Figure 7, a power failure can occur when two out of three power sources fail.

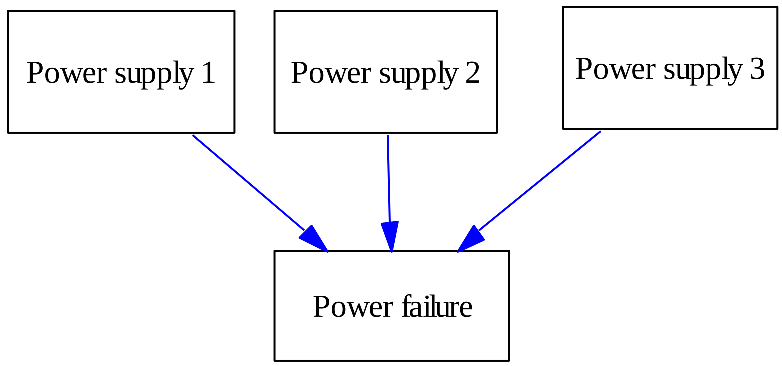


Figure 7: M from N operator example.

An important note to make here is that when M=1, it is equivalent to an OR operator and when M=N, it is equivalent to AND operator.

Noisy OR operator: The Noisy OR operator is used when the impact of each parent node on the child node is of a varying degree. For example, say that obesity is caused due to lack of exercise, improper diet and stress. However, each of these parent nodes can have a varying degree of impact. In such cases a Noisy OR operator is used. Each parent node is assigned with a number between 0 and 1. This number signifies the probability of occurrence of child node when parent node occurs. If there is a 30% chance that lack of exercise causes obesity then the number assigned to lack of exercise is 0.3. Additionally, a leak parameter is added to the model, which accounts for the noise in the model. This leak parameter represents additional causes leading to obesity, which have not been considered in the model.

(c) Numeric nodes: Numeric nodes are used in cases where numbers are required to represent the variable. These nodes are either discrete (number of defects, number of workers etc.) or continuous (level of water, height of workers etc.). When a particular system consists of both discrete and continuous nodes it is known as a hybrid system.

The relationships amongst nodes are defined through conditional probabilities. The conditional probability is the probability of child node *C* given that the parent node *Pt* is true and it is denoted as P(*Pt*|*C*). The relationships between nodes in BBNs are fundamentally based on the Bayes' theorem and can be stated as follows:

$$P(Pt\,|\,C) = \frac{P\left(C|Pt\right) * P\left(Pt\right)}{P\left(C\right)} \tag{1}$$

where, P(*Pt* | *C*) is the conditional probability of occurrence of parent node (*Pt*) given that child node (*C*) occurs. Similarly, P(*Pt*) and P(*C*) are probabilities of *Pt* and *C* occurring. Alternatively, P(*C* | *Pt*) is the probability of *C* given *Pt* occurs.

For risk assessment using BBN, each risk event is considered as a node and the complex relationships between these risk events is captured through conditional probabilities. A node probability table (NPT) is associated with each node/risk event as shown in Figure 8. This table defines relationship between the child node and its parent nodes using conditional probabilities.

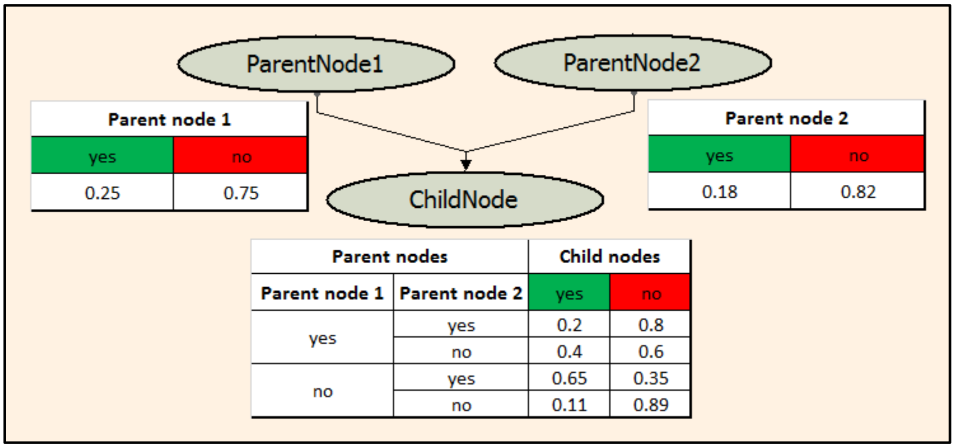


Figure 8: Sample Node Probability Table -BBN

From these NPTs, the probability of occurrence of child node is calculated using the chain rule application of Bayes theorem.

$$
\begin{aligned}
&P(C) = P(C \mid Pt1, Pt2) * P(Pt1) * P(Pt2) + P(C \mid \sim Pt1, Pt2) * P(\sim Pt1) * P(Pt2) \mid \\
&+ P(C \mid Pt1, \sim Pt2) * P(Pt1) * P(\sim Pt2) + P(C \mid \sim Pt1, \sim Pt2) * P(\sim Pt1) * P(\sim Pt2) \\
&P(C) = (0.2 * 0.25 * 0.18) + (0.65 * 0.75 * 0.18) + (0.4 * 0.25 * 0.82) + (0.11 * 0.75 * 0.82) \\
&= 0.2464
\end{aligned}
\tag{2}
$$

where, *C* is the child node occurring due to parent nodes *Pt1* and *Pt2*. P(*C*), P(*Pt1*) and P(*Pt2*) are probabilities of *C*, *Pt1* and *Pt2* occurring. The complement of these probabilities are represented as P(~*C*), P(~*Pt1*) and P(~*Pt2*). P(*C*|*Pt1*,*Pt2*) is the conditional probability of *C* when *Pt1* and *Pt2* are true. Alternatively, P(*C*|*Pt1*,~*Pt2*) is the conditional probability of *C* when *Pt1* is true and Pt2 is false and so on.

Additionally, the BBN allows back propagation which help in tracking the source of the problem. When the occurrence probability (posterior probability) of a child node is known, the probabilities of parent nodes can be updated using the reverse application of Bayes theorem. This helps a user to identify the possible root cause of a risk event.

In spite of the robust structure of BBNs, there are some concerns that need to be addressed before using it for risk assessment. BBN models are heavily dependent on the scope defined. As the scope increases, the number of nodes increase thus leading to an increase in the complexity of BBN models. Usually, BBN models are constructed by feeding both objective and subjective data. As the BBN size increases the objective data required can become very large making the process of data collection extremely cumbersome. Also, if the number of child nodes to a parent node increases, determining the conditional probabilities of each child can become unrealistic. This is another reason to clearly define the scope of risk assessment. When it comes to subjective data, the quality, diversity and number of industry experts/users interviewed can play a crucial role. Hence, the process of data collection needs to be well structured. In addition, computational abilities need to be taken into account when dealing with BBN models.

3.2.2. System Dynamics

System Dynamics (SD) is an approach to model and understand the behaviour of a complex system over a period. SD is a powerful tool to capture the non-linear behaviour of the system through SD feedback loops and delays. Sterman (2000) provides details on modelling using SD simulation. SD modelling follows a 2-step methodology:

(1) Causal Loop diagram

(2) Stock and Flow diagram

A causal loop diagram is used to visualize the causal relationships in a system. It consists of all the elements representing the system and their interactions with each other including feedback loops and time delays, which are an integral part of the system. It helps conduct a qualitative analysis of the system's structure and behaviour.

A simple example of a system represented using a causal loop diagram is demonstrated in Figure 9. Customer demand, manufacturing output and climate change are the three variables considered in a system. An increase in customer demand increases manufacturing output and vice-versa. This leads to a reinforcing feedback loop. Hence, a continuous growth pattern could be observed. Simultaneously, manufacturing output increases the risk of climate change. A time delay is used to represent this as climate change due to manufacturing output is a slow process. Additionally, climate change results in decrease in manufacturing output thus forming a balanced loop and both loops act simultaneously. Initially with increase in customer demand, manufacturing output increases. Eventually, manufacturing output subsides with climate change.

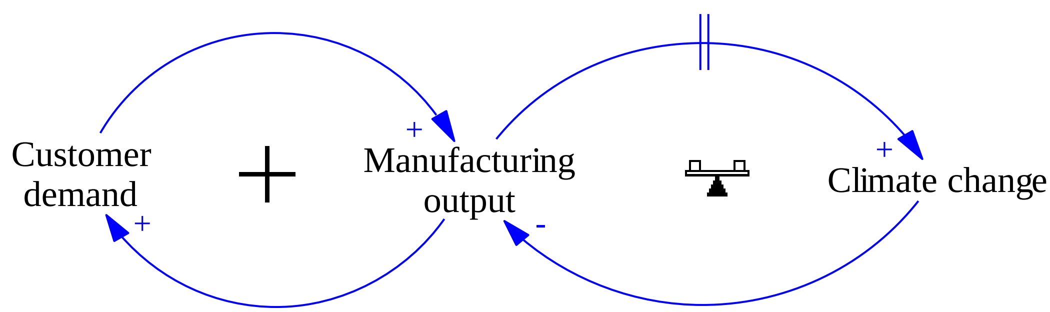


Figure 9: Causal Loop Diagram example.

A causal loop diagram is followed by stock and flow diagram. A stock and flow diagram is a quantitative analysis technique with the use of stocks and flows. Stocks are accumulations in the system and stocks are used to represent variables like inventories, revenue or any other variable that changes with time. Flows are entities that control these stocks. A flow entering a stock (*Entry_flow*) increases the value of a stock and a flow exiting a stock (*Exit_flow*) decreases its value. Mathematically, the relationship between stocks and flows is shown in equation (3) below.

$$Stock = \int_0^t (Entry\_flow - Exit\_flow)dt \tag{3}$$

A causal loop diagram is transformed into a stock and flow diagram as shown in Figure 10 below. Customer demand leads to growth in manufacturing output at a certain rate. This, in turn, promotes customer demand. The growth in manufacturing output negatively impacts the climate at a rate represented by the decline rate. Initially, growth rate will be far more than the decline rate, leading to an increase in manufacturing output. However, as the rate of decline increases, manufacturing output will be stalled and then start declining.

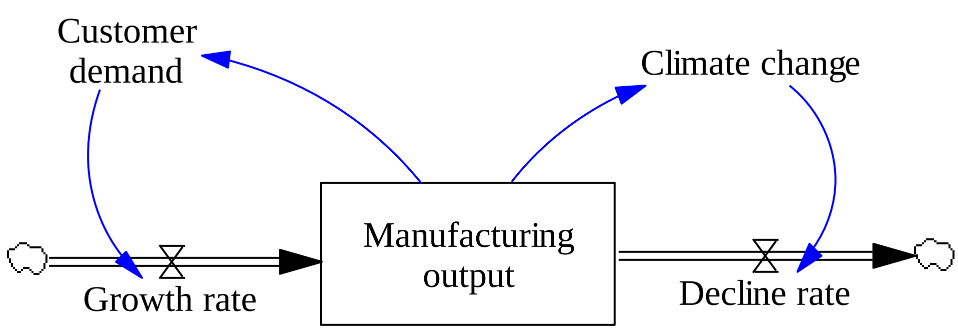


Figure 10: Stock and Flow Diagram Example.

Simulating stock and flow model computes data regarding the performance of the system for the simulated time period. Analyzing this data provides insight into the behavior of the system. System Dynamics captures the non-linear nature of the system in an effective way.

3.2.3. Bayesian-Integrated System Dynamics

BBNs are a powerful way of capturing the probabilistic nature amongst risk events. BBN models help quantify risks and capture relationships amongst them. A BBN's inability of capturing the dynamic nature of production line risk is enhanced in this research by combining it with an SD model. Combining BBN with SD production line model provides capabilities such as feedback loops and delays to the BBN risk model helping capture the dynamic nature of risk events. Additionally, SD production line model's ability to integrate KPIs and to perform several what-if scenarios helps gain a better understanding of the system's behaviour.

A methodology is proposed here to facilitate the interaction between BBN risk model and SD production line model. Vensim, an SD software, allows its users to construct a model with user defined variables and functions easily. This allows to create the BBN risk model and SD production line model within Vensim. To improve visualization of complex models, Vensim has a provision for dividing the model into several subsets known as views. The BBN model is constructed in one such view and the SD production line model in another view. The interaction between the views occurs through shadow variables which are the variables from another view interacting with the variables of the current view.

Each risk event in the BBN model and their conditional probabilities are represented as variables. Arcs are used to connect these variables. Figure 11 shows the representation of BBN in SD software (Vensim). Parent risk event 1 (RE1) and risk event

2 (RE2) are connected to child risk event 3 (RE3) using arcs. Their corresponding probabilities are P(RE1), P(RE2) and P(RE3). The complement of these probabilities are denoted as P(~RE1), P(~RE2) and P(~RE3). P(RE3|RE1,RE2) is the conditional probability of RE3 given RE1 and RE2 are true. Similarly, P(RE3|RE1,~RE2) is the conditional probability of RE3 given RE1 is true and RE2 is false. P(RE3|~RE1,RE2) is the conditional probability of RE3 given RE1 is false and RE2 is true. P(RE3|~RE1,~RE2) is the conditional probability of RE3 given RE1 and RE2 are false. The likelihood of each risk event and their conditional probabilities are represented as variables.

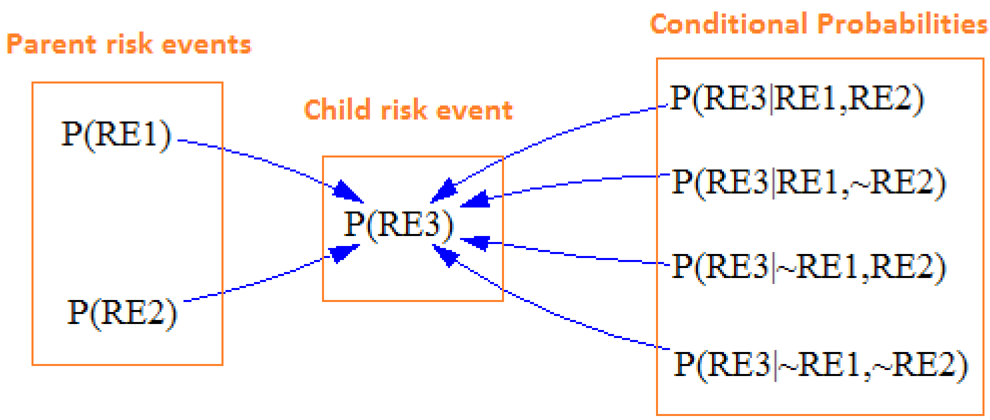


Figure 11: Representing BBN in System Dynamics.

For the child nodes, the conditional probabilities are calculated using the chain rule application of Bayes' theorem. For example, the probability of risk event 3 (*P(RE3)*) can be computed as shown in equation (4):

$$\begin{aligned} P(RE3) &= (P(RE3) \mid RE1, RE2) * P(RE1) * P(RE2)) + (P(RE3) \mid \sim RE1, \sim RE2) * (1 - P(RE1)) * (1 - P(RE2))) \\ &+ (P(RE3) \mid \sim RE1, RE2) * (1 - P(RE1)) * P(RE2)) + (P(RE3) \mid RE1, \sim RE2) * P(RE1) * (1 - P(RE2))) \end{aligned}$$

(4)

The BBN model is then connected to the production line SD simulation model to assess the impact of risk events on the production line over the simulation period.

When child risk events occur, they can trigger various adverse impacts on the production line. This is modelled in SD by identifying the most likely production line variable to be impacted by each child node and then capturing it by a user-defined equation.

SD facilitates modelling of a production line through stocks and flows. Stocks are accumulations of system variables, similar to inventories. These stocks/inventories are controlled through flows, similar to production rates. Rehab (2014) demonstrates an effective method for the construction and analysis of a lean manufacturing system using SD. This method could be used in construction of production line model. Figure 12 shows the construction of a production line model. The model consists of three workstations through which raw material gets processed. Raw material is represented as a stock and procurement rate is the flow that controls the quantity of raw materials available. Work in process (WIP) at station 1 is represented as stock controlled by procurement rate and production rate at station 1. If procurement rate is greater than production rate at station 1 then WIP at station 1 increases. Alternatively, if production rate at station 1 is higher than procurement rate then WIP at station 1 decreases. The WIP at station 2 is controlled by production rates at station 1 and station 2. The WIP at station 3 is controlled by production rates at station 2 and station 3.

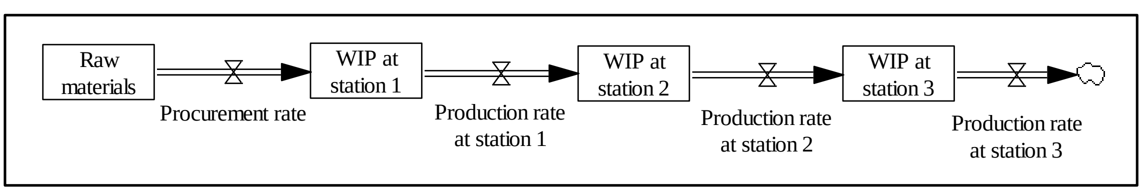


Figure 12: System Dynamics production line model

This production line model is considered to be the baseline model. The baseline model is built using system variables without considering the effects of risk events. It is this baseline model that helps compare results from both cases and highlights the significance of risk assessment. It is important to note that baseline model is not based on ideal values of system variables. Natural variation occurring in system variables is considered while building the baseline model.

The baseline model is simulated and its results are recorded. In order to observe the effects of risk events on the baseline model, the BBN model is connected to the SD production line model. The BBN model calculates the likelihood of child risk events based on their causal relationships with parent nodes and the prior probabilities entered. Based on this likelihood of the child risk event, the severity of risk event is calculated. Given the scope of the study is the production line level, some form of proportionality is anticipated between likelihood and severity of risk events. This relationship is captured through the use of a lookup function or table function and can be developed using expert opinion. The relationship can be entered in the form of table function by associating a severity (in terms of production loss) with a likelihood range. For example, when *P(RE3)* is between 0 to 0.1, the severity of the risk event 3 is loss of 200 parts. Similarly, when *P(RE3)* is between 0.2-0.3 then the severity of risk event 3 is assumed to be a loss of 250 parts. The BBN risk model is connected to the SD production line model through a production line variable. The production line variable is impacted by both the likelihood and severity of risk event. Equation 5 shows the calculation of the risk event impact using the function "*PULSETRAIN*", an in-built Vensim function that relates the impact frequency (1/*P(RE)*) and the severity of risk event:

$$Risk\_event\_impact = PULSETRAIN(impact\_start\_time, impact\_duration, impact\_frequency, final\_time) * Severity\_of\_risk\_event. \quad (5)$$

where, *impact_start_time* is the time when first risk event occurs, *impact_duration* is the duration for which the risk event lasts for upon occurrence and *impact_frequency* is the frequency at which risk events occur which is the inverse of risk likelihood calculated from BBN risk model. *Final_time* is the end of simulation time period. *Severity_of_risk_event* is developed by expert opinion as discussed above.

PULSE is a Vensim function that returns 1 when current time (*time*) is greater than a pre-determined time (*start_time*) from which PULSE function is to be activated and less than the sum of *start_time* and duration for which a time interval lasts (*interval_width*). For example, if a simulation time period is for 50 days and PULSE function is to be used for an event occurring after 20th day and lasting for 2 days then the *start_time* would be 20 and *interval_width* would be 2. PULSE function would return the number 1 on 21st and 22nd day of the simulation time period. Equation 6 describes the math behind PULSE function.

$$If\_then\_else((start\_time + interval\_width) > time > start\_time, 1, 0) \quad (6)$$

A train of repeated pulses is known as PULSETRAIN function.

In order to capture the dynamic nature of risk events, a response variable is triggered to alter the nature of risk events through the production line model. Usually, KPIs are the system variables that trigger a response variable. Figure 13 shows an example where

RE3 is the risk event that impacts the production line variable (related to production rate at station 1). The impact of risk events on the production line is monitored at the station 3 through a KPI. When the KPI value increases/decreases beyond a certain limit, it is setup to initiate a risk management (RM) process. The RM reduces the likelihood of the RE3. Equation 7 shows how *P(RE2)* is impacted by RM. A residual risk is associated with the risk event, which can be determined by the use of data and/or expert judgement. *P(RM)* drives *P(RE2)* such that when *P(RM)* is 0, *P(RE2)* remains unchanged and when *P(RM)* is 1, *P(RE2)* is equal to residual risk.

$$P(RE2) = P(RE2) * (1 - P(RM)) + (\mathrm{Re}\,sidual\_risk * P(RM)) \tag{7}$$

This change in value of *P(RE2)* is reflected on *P(RE3)* and thus, establishing a feedback loop.

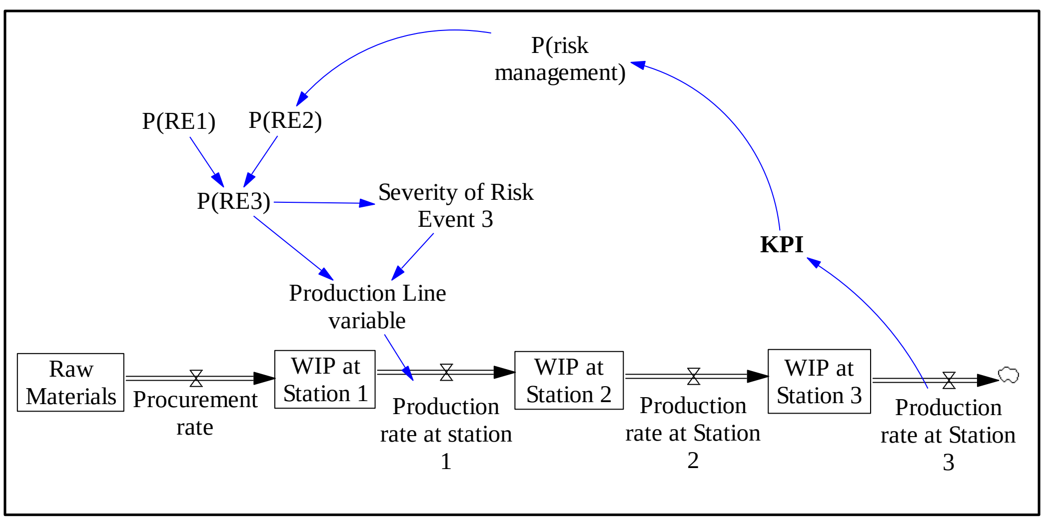


Figure 13: Interaction between BBN and SD model.

3.3. Risk Evaluation

The impact of the risk events on the production line KPIs is examined for risk evaluation. KPIs give a holistic idea about the behaviour of the system and aids management in decision-making. In addition, SD provides a platform to analyze the system under several scenarios. Evaluating the system under several scenarios, realistic and far-fetched, can help gain further insight into the behavior of the system and enable companies to prepare for radical or extreme situations.

4. Application of Methodology

4.1. Case Study Overview

The automotive industry is one of the most competitive industries in the manufacturing sector. In this research a case study from the automotive industry is used to demonstrate the application of the proposed method.

A growing supplier of precision metal components and assemblies using fineblanking technology was considered to apply the methodology proposed for production line risk assessment. The company operates plants at several locations across the globe including US, Canada, Mexico and China. The company name and other information is withheld due to confidentiality reasons.

One of the divisions in the company's US facilities specializes in producing several kinds of engine plates and transmission parts, which are supplied to major automobile manufacturers. One of the major and strategically important customer's products, Engine Plates, was selected for study in this research. The processes/stations through which the raw material is converted into finished good and sent to the customer are listed in the process routing sheet (provided by the company). Production capacities at each station is calculated by the ERP software, PLEX, by collecting real time data. Sources for other data are mentioned in the following sections, where relevant.

The process routing for producing engine plates and the production capacity at each step is provided in Table 3. The engine plates are first fineblanked in a hydraulic press followed by drilling operation where holes are drilled using a drill press. This is followed by tapping and countersink operations. After secondary machining, engine plates go through finishing operations of grinding and beltsanding. After finishing processes, these plates go for inspection and to the packing station, ultimately reaching shipping area. Fineblanking is the second quickest operation with a mean production capacity of 3200 parts/day. Drilling, Tapping and Countersink operations re slightly behind with a mean production capacity of 2610 and 2465 parts/day respectively. Grinding operation is the bottleneck operation with a mean production capacity of just 1740 parts/day. The following process of Beltsand and Brush is the quickest operation with a mean production capacity of 7250 parts/day. This is followed by inspection and packing where the mean production capacity is slightly higher than that of the Grinding operation at 1900 parts/day. Shipping can handle 5500 parts/day.

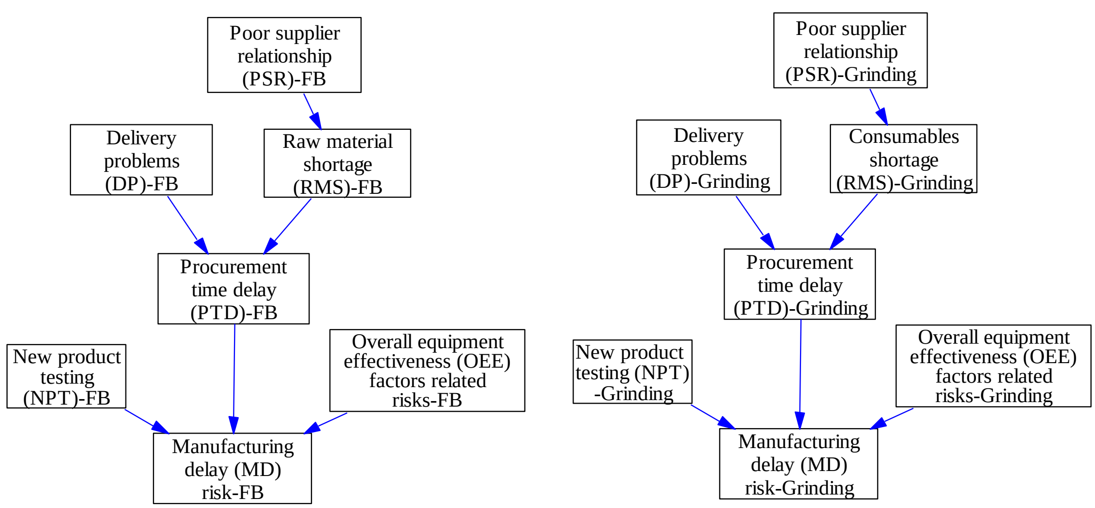
Table 3: Process routing of engine plates.

S.no.	**Process Step**	**Production Capacity (parts/day)**
1	Fineblanking	Normal dist.(3200,50)
2	Drilling	Normal dist.(2610,25)
3	Tapping and Countersink	Normal dist.(2465,25)
4	Grinding	Normal dist.(1740,10)
5	Beltsand and Brush	Normal dist.(7250,25)
6	Inspection and Packing	Normal dist.(1900,10)
7	Shipping	5500

4.2. Risk Identification

A Risk Network map of risks impacting the production line was developed with the help of industry personnel. General operational risks identified by Badurdeen et. al., (2014) were referred during this phase.

It was discerned that manufacturing disruptions or delays are the primary risks impacting production line as shown in Figure 14. New product testing (NPT), procurement time delays (PTD) and the overall equipment effectiveness (OEE) factors, which are availability, performance and quality, related risks are the major risk events leading to the manufacturing delay (MD) risk. On the other hand raw material shortages (RMS), caused by poor supplier relationship (PSR), and delivery problems (DP) were found to be the major risk events leading to the procurement time delay (PTD) risk event at the fineblanking station. Alternatively, consumables shortage (CS), caused by poor supplier relationship (PSR), and delivery problems (DP) were found to be the major risk events leading to the procurement time delay (PTD) risk event at the grinding station.



(a): Fineblanking station (b): Grinding station

Figure 14: BBN risk model for Case study.

Impact of risk events on the production line is considered at the fineblanking station and grinding station. The fineblanking station was strategically targeted as it is the first stage of the production line and has the highest value addition. The grinding station is selected as it is the bottleneck station and affects the overall throughput of the production line.

4.3. Risk Assessment

Vensim, an SD software, is used to develop the BBN and production line models. Figure 15 shows a causal loop diagram for the case study. The cause-effect relationship between risk events from BBN model and production line variables from production line SD model are represented in the figure.

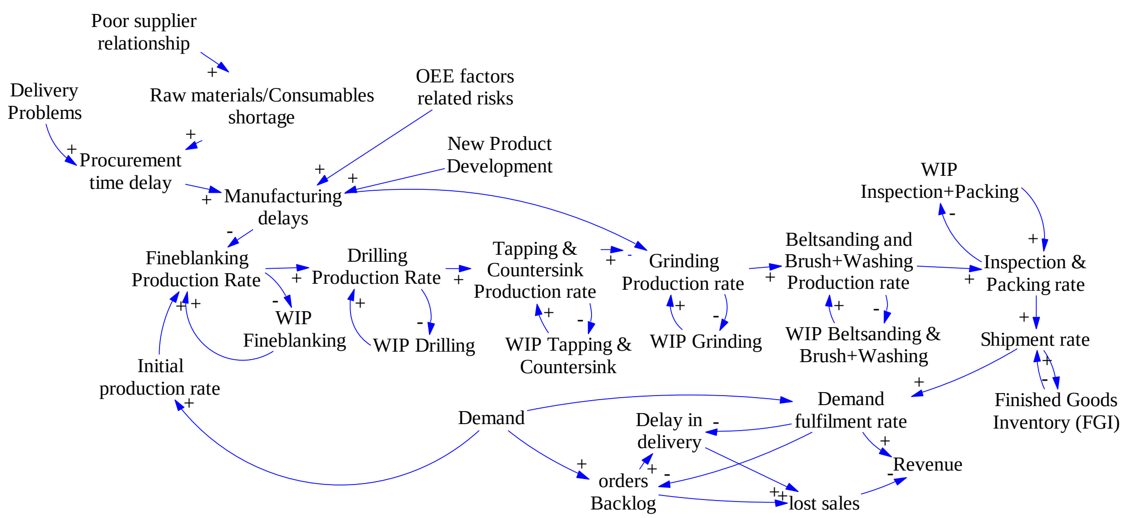


Figure 15: Causal loop diagram- Case study

Based on the causal loop diagram shown in Figure 16, the BBN and the production line SD models are developed. The BBN model consists of risks identified in step1.

Tables 4-8 display the prior probabilities of risk events at fineblanking station and Tables 9-13 display data used at grinding stations. The data required to construct these node probability tables were obtained by utilizing resources within the company and consulting with the managers.

Table 4: Prior probabilities for poor supplier relationship and new product testing at fineblanking station.

Nodes	Yes	No
Poor supplier relationship	0.2	0.8
New product testing	0.38	0.62

Table 5: Node probability table for poor supplier relationship and raw material shortage at fineblanking station.

Parent node	**Raw material shortage**	
Poor supplier relationship	Yes	No
Yes	0.5	0.5
No	0.2	0.8

Table 6: Node probability table for raw material shortage, delivery problems and procurement time delay at fineblanking station.

<table>
<tr><td colspan="2">Parent nodes</td><td colspan="2">Procurement time delay</td></tr>
<tr><td>Raw material shortage</td><td>Delivery Problems</td><td>Yes</td><td>No</td></tr>
<tr><td rowspan="2">Yes</td><td>Yes</td><td>0.72</td><td>0.28</td></tr>
<tr><td>No</td><td>0.65</td><td>0.35</td></tr>
<tr><td rowspan="2">No</td><td>Yes</td><td>0.6</td><td>0.4</td></tr>
<tr><td>No</td><td>0.1</td><td>0.9</td></tr>
</table>

Table 7: Prior probabilities for poor supplier relationship and new product testing at fineblanking station.

Nodes	Min	Max	Mean	Standard deviation
Delivery Problems	0.3	0.8	0.55	0.05
OEE factors related risks	0.4	0.85	0.5	0.15

Table 8: Node probability table for PTD, NPT, OEE factors related risks and MD at fineblanking station.

Parent nodes			Manufacturing delay	
Procurement time delay	**New product testing**	**OEE factors related risks**	Yes	No
Yes	Yes	Yes	0.9	0.1
		No	0.54	0.46
	No	Yes	0.42	0.58
		No	0.2	0.8
No	Yes	Yes	0.66	0.34
		No	0.25	0.75
	No	Yes	0.22	0.78
		No	0.05	0.95

Table 9: Prior probabilities for poor supplier relationship and new product testing at grinding station.

Nodes	Yes	No
Poor supplier relationship	0.25	0.75
New product testing	0.45	0.55

Table 10: Node probability table for poor supplier relationship and consumables shortage at grinding station.

Parent node	Consumables shortage	
Poor supplier relationship	Yes	No
Yes	0.4	0.6
No	0.04	0.96

Table 11: Node probability table for Consumables shortage, delivery problems and procurement time delay at grinding station.

Parent nodes		**Procurement time delay**	
Consumables shortage	**Delivery Problems**	Yes	No
Yes	Yes	0.6	0.4
	No	0.3	0.7
No	Yes	0.3	0.7
	No	0.05	0.95

Table 12: Prior probabilities for poor supplier relationship and new product testing at grinding station.

Nodes	Min	Max	Mean	Standard deviation
Delivery Problems	0.2	0.6	0.4	0.05
OEE factors related risks	0.3	0.65	0.42	0.12

Table 13: Node probability table for PTD, NPT, OEE factors related risks and MD at grinding station.

Parent nodes			**Manufacturing delay**	
Procurement time delay	**New product testing**	**OEE factors related risks**	Yes	No
Yes	Yes	Yes	0.9	0.1
		No	0.42	0.58
	No	Yes	0.38	0.62
		No	0.15	0.85
No	Yes	Yes	0.65	0.35
		No	0.28	0.72
	No	Yes	0.2	0.8
		No	0.05	0.95

This is followed by developing the SD production line model as shown in Figure 16. Each station has a production capacity, which is the maximum output at the workstation without considering risk events and WIP constraints. Production capacities follow a normal distribution, as shown in Table 3, obtained through comprehensive time studies performed on several operators. In addition, data from previous time studies performed by the sales & accounting departments, for business planning purposes, are used. Actual production rate at each station depends on the minimum of WIP quantity at the station and production capacity. WIP at each station is computed based on the difference between entry and exit production rates at that station.

The inspection and packing station performs a quality check. Defective products are reworked and introduced back to the production line. The defects percentage is obtained through the quality reports at the inspection station.

The demand follows a Normal distribution with a mean of 1724 parts/day and standard deviation of 35 parts. It was obtained from demand forecasts calculated by the sales department. Demand fulfilment rate is equal to the shipment rate. Order backlog is based on the difference between demand fulfilment rate and demand. Delay in delivery is equal to order backlog divided by demand fulfilment rate. Revenue is calculated as the difference between revenue made from sales and lost sales.

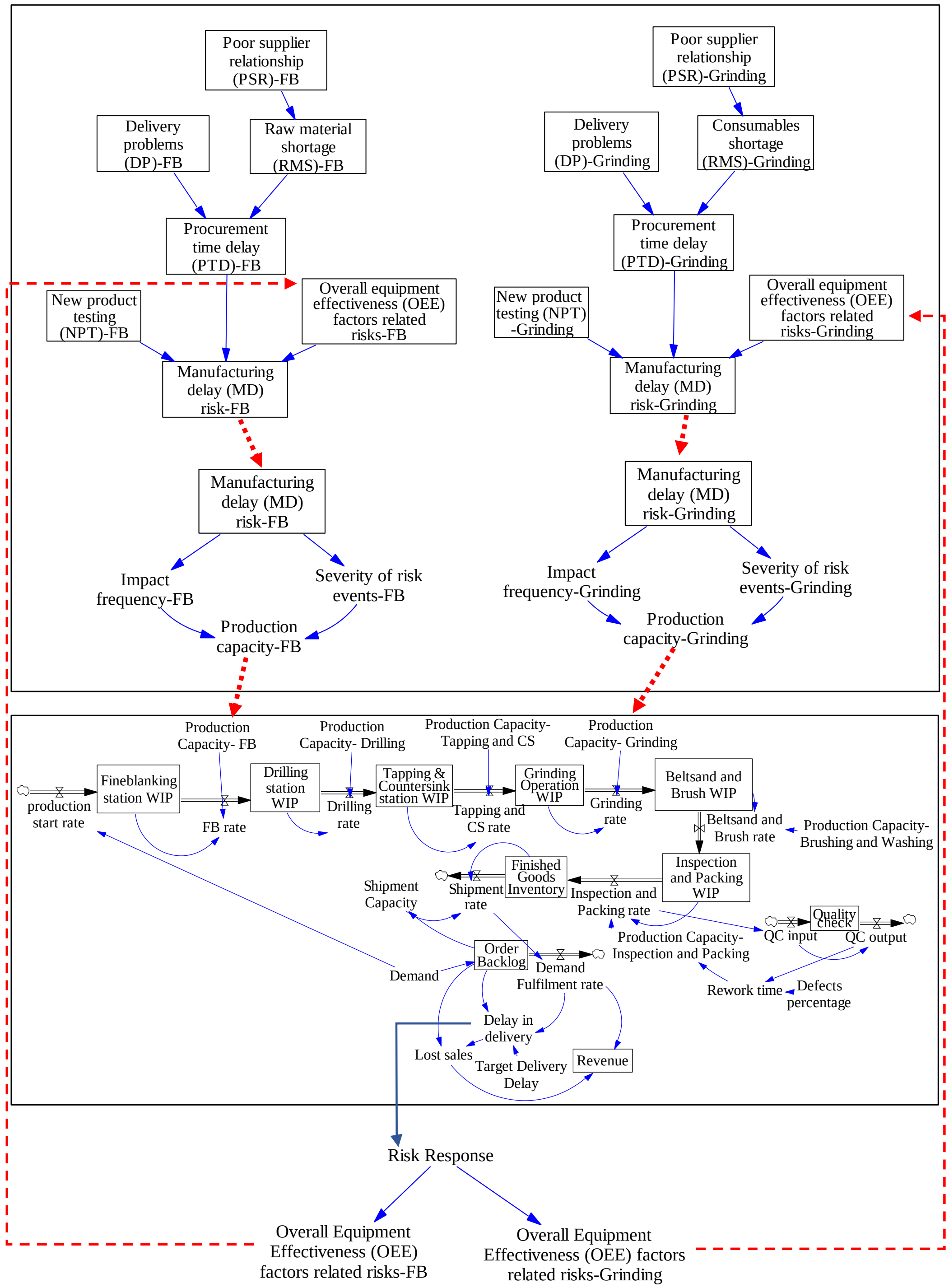


Figure 16: BBN-Integrated SD modelling for Case study

This production line model could also be considered as the baseline model. Baseline model produces results similar to the business plan for the year and what the industry personnel expect to see without any risks. The baseline production model is then connected to the BBN model for risk assessment as shown in Figure 16. The manufacturing delay risk likelihoods (fineblanking and grinding), calculated from BBN model, forms the basis for impact frequency at the fineblanking and grinding stations. The Severity of risk events is estimated with the help of industry personnel. Since the scope of the risk assessment is at the production line level, proportionality is assumed between severity of risk events and risk likelihood. Table 14 displays the relationship between the risk likelihood and severity of the risk at fineblanking and grinding stations.

To incorporate the impact due to risk events, the production capacity equation is modified by subtracting the baseline production capacity with the risk event impact (quantified in terms of production rate loss). Equation 5 is used to calculate the risk event impact.

Table 14: Relationship between manufacturing delay risk and severity of risk event at fineblanking and grinding stations.

Fineblanking station		Grinding station	
Manufacturing delay risk	Severity of risk event (parts)	Manufacturing delay risk	Severity of risk event (parts)
0	0	0	0
0.05	0	0.05	0
0.1	0	0.1	0
0.15	0	0.15	0
0.2	500	0.2	200
0.25	1000	0.25	200
0.3	1000	0.3	450
0.35	1000	0.35	450
0.4	2000	0.4	450
0.45	2000	0.45	450
0.5	2500	0.5	900
0.55	2500	0.55	900
0.6	2500	0.6	900
0.65	2500	0.65	900
0.7	2750	0.7	900
0.75	2750	0.75	1340
0.8	2750	0.8	1340
0.85	3000	0.85	1340
0.9	3000	0.9	1340
0.95	3000	0.95	1800
1	3000	1	1800

The dynamic nature of risk events is captured through risk response variable as shown in Figure 16. Risk response is triggered by the "Delay in delivery" performance indicator. A proportional relationship is defined, as shown in Table 15, between risk response variable and "Delay in delivery" performance indicator. This risk response variable mitigates or reduces the likelihood of OEE factors related risks as it is within the scope of the production team. The model is then simulated for a long duration to observe the changes in the behavior of the system. 400 days was chosen as the ideal simulation period as this would give the model enough time to experience effect of risk events and the response triggered by poor performance. This would, in turn, help in assessing the system more accurately.

Table 15: Relationship between delay in delivery and risk response variable.

Delay in delivery	Risk Response	Delay in delivery	Risk Response
0	0	5.5	0.4
0.5	0	6	0.4
1	0	6.5	0.4
1.5	0.05	7	0.5
2	0.1	8	0.5
2.5	0.15	9	0.5
3	0.2	10	0.75
3.5	0.25	11	0.75
4	0.25	12	0.9
4.5	0.35	13	0.9
5	0.35	14	1

4.4. Risk Evaluation

System Dynamics allows users to run various scenarios and obtain a comprehensive understanding of the system's behaviour. The case study company managers are interested in the possibility of testing scenarios based on variation in the OEE risk and response time towards risk impact. Table 16 shows the two states chosen for the OEE factors related risk variable and response time decided in consultation with industry personnel. The two states chosen are normal and high. Under the high state, mean OEE factors related risk is 0.75. Response time is the time taken for the risk response activities to take place and show a difference on the risk likelihood of OEE factors related risk. Under normal state, response time is 1 week and it is 1 month when the state is high. Table 17 presents the 16 what-if scenarios that were run on the model.

Table 16: Variables and alternate states for testing.

Station	Risk events	Normal	High
Fineblanking Station	OEE risk	mean: 0.5	mean: 0.75
	Response time	1 week	1 month
Grinding Station	OEE risk	mean: 0.42	mean: 0.75
	Response time	1week	1 month

Table 17: Scenarios used for case study

S.No.	**Fineblanking station**		**Grinding station**	
	OEE risk	**Response time**	**OEE risk**	**Response time**
1	Normal	Normal	Normal	Normal
2	High	Normal	Normal	Normal
3	High	Delayed	Normal	Normal
4	Normal	Delayed	Normal	Normal
5	Normal	Normal	High	Normal
6	Normal	Normal	High	Delayed
7	Normal	Normal	Normal	Delayed
8	Normal	Delayed	Normal	Delayed
9	High	Normal	High	Normal
10	High	Normal	High	Delayed
11	High	Delayed	High	Delayed
12	Normal	Delayed	High	Delayed
13	Normal	Delayed	High	Normal
14	High	Normal	Normal	Delayed
15	High	Delayed	Normal	Delayed
16	High	Delayed	High	Normal

5. Results and Discussion

5.1 Establishing Baseline

Simulation of production line without considering the effects of risk events helps verify the model and to establish a baseline. Results from this simulation reflect the expectations from the line and provide a basis to compare different scenarios.

A variety of KPIs were studied to comprehend the behaviour of the production line.

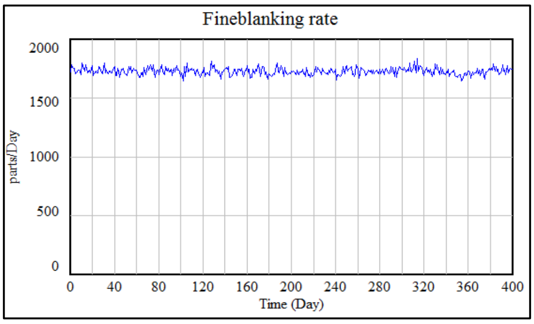
Delay in delivery: This is the most customer orientated KPI and is a reflection of the overall performance of the production line. It is important to have a low delay in delivery to maintain a good relationship with customers. In the baseline scenario, production capacities at each station are adequate to fill customer orders on time and hence, there is no delay in delivery.

Production rates: Although delay in delivery reflects the overall performance of the production line, it does not reveal details about the efficiency of workstations. Production rates at fineblanking and grinding stations were of primary concern given their importance. Fineblanking is the most value adding process in the routing and the most critical operation. Grinding station is the bottleneck operation. Hence, the production rates at this station dictate the overall throughput of the line.

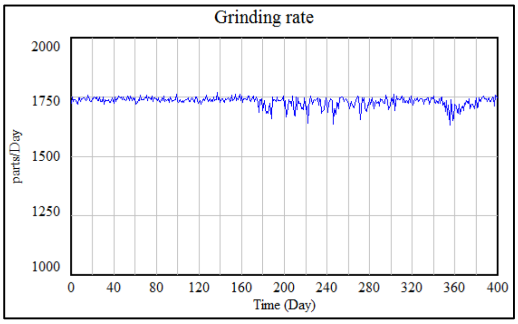
Figure 17(a) displays the fineblanking station performance. Fineblanking performance remains consistent throughout the 400 day period with peak production on the 45^{th} day at 1859 parts. Due to its high production capacity of 3200 parts/day, fineblanking rate is equal to the demand for the product. Figure 17(b) displays grinding station throughput. Grinding also remains consistent through the 400 day period.

Although grinding capacity is not equal to peak demand, WIP at grinding station helps in meeting demand and avoid a delay in delivery.

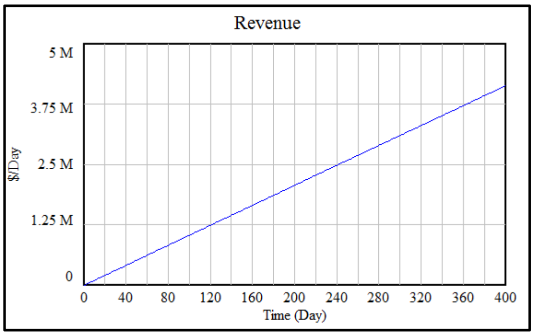
Revenue: Revenue is another key indicator. Revenue generated indicates the profitability of the production line. Overall revenue from sales for the simulation period was at $4.1792 million. Since there was no delay in delivery, revenue curve is a linear equation.



(a) Baseline- Fineblanking rate



(b) Baseline- Grinding rate



(c) Baseline-Revenue

Figure 17: Key performance indicators for baseline scenario

5.2 Risk Analysis for Different Scenarios

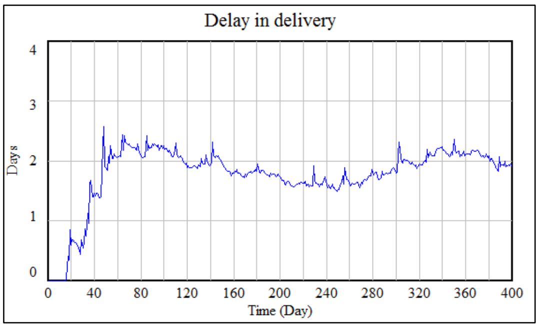
Following the analysis of the baseline scenario, the production line model was subjected to risk events to study other scenarios described in Table 8. Behavior of the production line system was assessed based on varying intensity of risk likelihood and response towards these risk events. The delay in delivery was chosen to be the best performance indicator to analyze the difference between each scenario as it reflects the overall performance of the production line, profitability and customer satisfaction. This analysis revealed some interesting trends in the system’s behaviour. Some of these observations are recorded below.

5.2.1 Comparison of “Delay in delivery” Performance

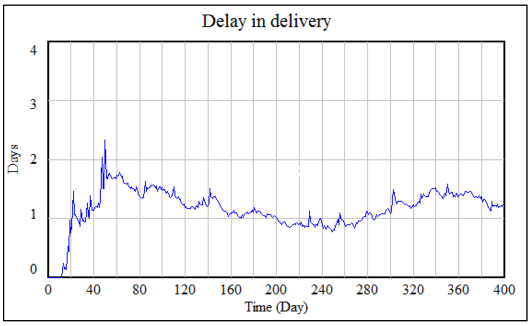
Observation 1: Scenario 1 has a higher delay in delivery compared to scenario 2 despite having a lower risk likelihood as shown in Figures 18(a) and 18(b). This was in contrast with the expectation of a higher delay in delivery when the production line is subjected to higher manufacturing delay risk. After analyzing the data, it was inferred that an increased risk likelihood results in an increase in risk response. With a higher risk at the fineblanking station in scenario 2, the delay in delivery is quite high initially. This high delay increases risk response, and this in turn, results in increased risk mitigation. Due to the increased risk mitigation, “Delay in delivery” in scenario 2 is much lower when compared to that of scenario 1 in the latter part of the simulation.

Observation 2: Contrary to the previous observation, scenario1 & scenario 5, depicted in Figures 18(a) and 18(d), show a different trend. A high risk likelihood at the grinding station results in a higher delay in delivery. The reason for this is that the grinding station is the bottleneck operation. A high manufacturing delay risk at the grinding station resulted in aggressive risk response. However, the delay in delivery was high and did not follow the pattern as seen in observation 1. A high risk likelihood at the grinding station (bottleneck operation) caused a drastic impact on the production line which couldn’t be compensated with the risk response activities.

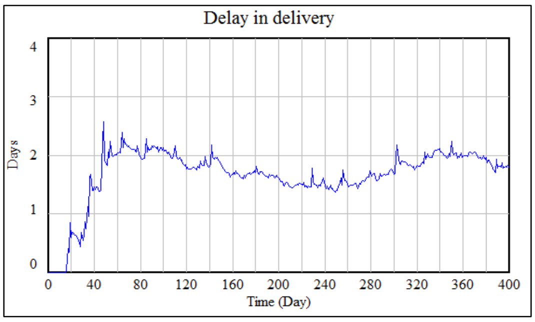
Observation 3: Scenario 4 shows a slightly higher delay in delivery when compared to scenario 1 as displayed in Figures 18(a) and 18(c). In general, an increase in risk response time leads to an accumulation of problems and increased manufacturing delays, which would in turn cause delay in delivery. However, the data suggests that a delayed risk response at the fineblanking station acts in favour of the company's cause. Although, a delayed risk response increases manufacturing delays and delay in delivery initially, it also increases the risk response and this leads to a decrease in likelihood of OEE factors related risk. This, in turn, reduces manufacturing delay risk likelihood and makes the production line run efficiently for the remainder of the simulation period.



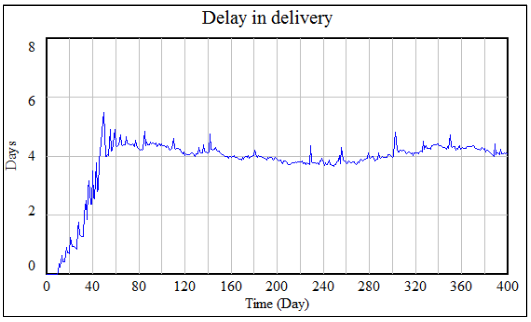
(a) Scenario 1



(b) Scenario 2



(c) Scenario 4



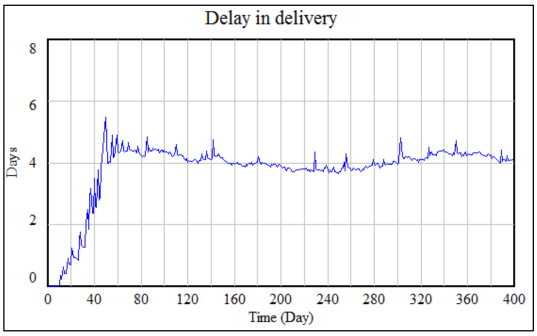
(d) Scenario 5

Figure 18: Delay in delivery performance for scenarios 1,2,4 and 5.

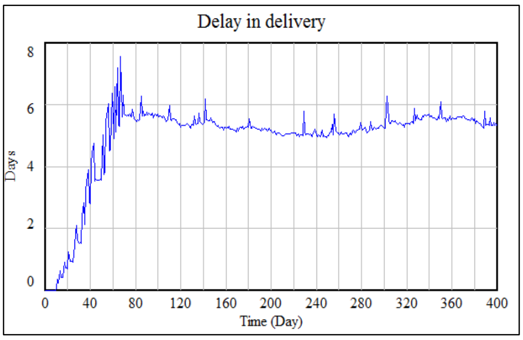
Observation 4: On the other hand, scenario 5 & scenario 6, displayed in Figures 19(a) and 19(b), show a different trend. In scenario 5, the impact of high risk likelihood at the grinding station causes a huge delay in delivery. The risk response activities resulting from delay in delivery was not enough for the production line to recover from this impact. A delayed risk response in scenario 6, does not make much difference.

With a delayed response, there is a difference of only ¾ days towards the end of the simulation period. Hence, it can be concluded that resources need to be spent to avoid the situation of a high risk likelihood at the grinding station.

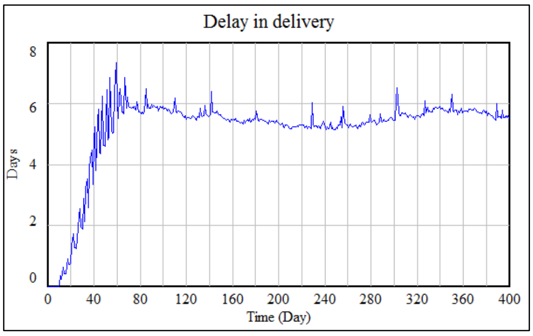
Observation 5: Before analyzing scenarios, the production line was expected to experience maximum delay in delivery when there is a high risk likelihood and delayed risk response at both fine-blanking and grinding station (scenario 11). However, scenario 10 shows a higher delay in delivery when compared to scenario 11 as displayed in Figures 19(c) and 19(d). A higher manufacturing delay risk at both fineblanking and grinding stations leads to a serious impact on the production line. This impact results in an aggressive risk response. In scenario 11, a delayed risk response considers the risk events occurring during this delayed period and hence results in higher risk response. Hence, delay in delivery is a little lower when compared to that of scenario 10.



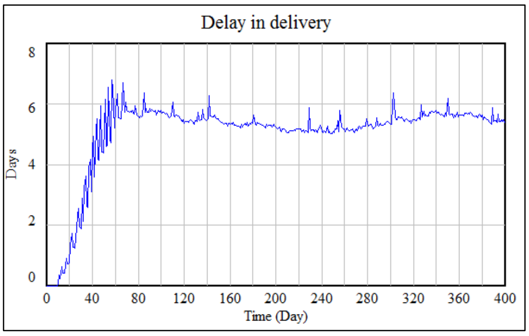
(a) Scenario 5



(b) Scenario 6



(c) Scenario 10

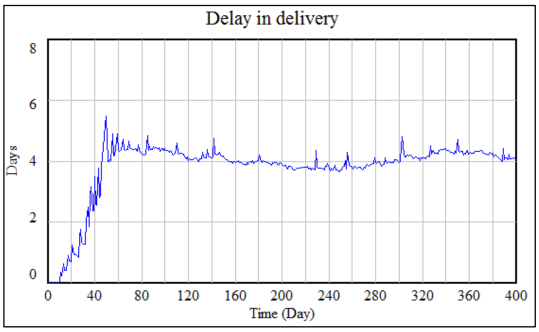


(d) Scenario 11

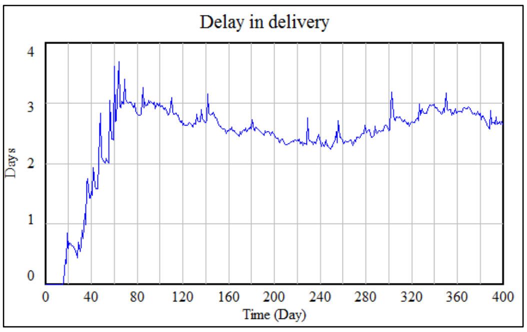
Figure 19: Delay in delivery performance for scenarios 5,6,10 and 11.

Observation 6: From Figures 20(b) and 20(d), scenario 7 has a higher delay in delivery when compared to scenario 14 despite having a lower manufacturing delay risk likelihood. The high risk likelihood results in a higher delay in delivery initially. This results in higher risk response, which drives down manufacturing delay risk likelihood. Hence, delay in delivery in scenario 14 is lower than that of scenario 7.

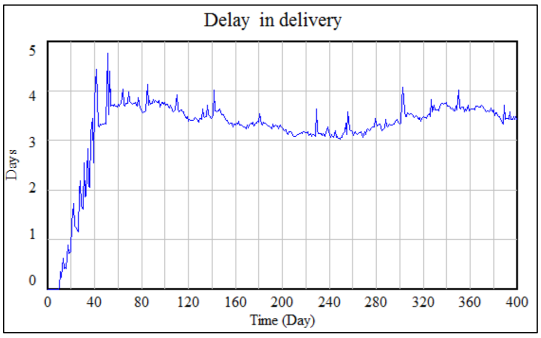
Observation 7: Scenario 5 shows a higher delay in delivery than in case of scenario 9 despite having a high risk at just the grinding station. Scenario 9, displayed in Figure 20(c), has a higher risk at both fineblanking and grinding stations resulting in a higher "Delay in delivery" initially. This results in an increase in risk response and thus leads to risk mitigation. Hence, a lower delay in delivery is seen towards the latter part of simulation in scenario 9.



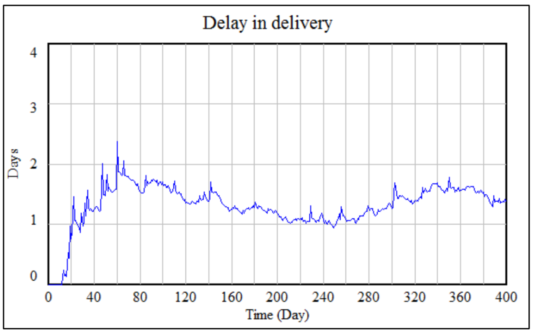
(a) Scenario 5.



(b) Scenario 7.



(c) Scenario 9.



(d) Scenario 14.

Figure 20: Delay in delivery performance for scenarios 5,7,9 and 14.

Although delay in delivery is an effective KPI to compare between scenarios, it cannot help the user to comprehend system's behaviour without additional support. A good delivery performance might not necessarily mean a good process and a bad delivery performance might not necessarily mean a non-profitable process. Apart from delay in delivery performance indicator, performance indicators like revenue, demand fulfilment rate, production rates and manufacturing delay risks at fineblanking & grinding stations, provide further insight into the system. It is necessary to consider the above mentioned KPIs to evaluate overall performance of the line.

To avoid redundancy, a selected set of scenarios were analyzed based on the realistic nature of the scenarios and their potential threat to the production line.

5.2.2 Analyzing Scenarios using all Key Performance Indicators.

Scenario 1:

Delay in Delivery: Initially, demand is fulfilled with the help of inventory and production. From Figure 21(a) delay in delivery occurs on the 16th day and continues until the end of simulated time period. Delay in delivery increases to 2 days and then starts declining due to risk response activities taking place. After 251st day, delay in delivery increases slightly with occurrence of risk events and then decreases again towards the end of the simulation period.

Demand vs Demand fulfilment rate: Demand fulfilment rate is the final throughput of the production line. As shown in Figure 21(b) the demand fulfilment rate reduces due to occurrence of risk events. Initially, the impact of risk events is compensated by production and inventory. After a period, risk events begin to impact production rates. The demand fulfilment rate fluctuates heavily in this period. With risk management activities taking place, this variation reduces to a significant extent.

From this graph, it could be concluded that major delay in delivery occurs during the period when risk likelihood is high. This delay in delivery continues until the end of simulation period due to lack of high production capacity.

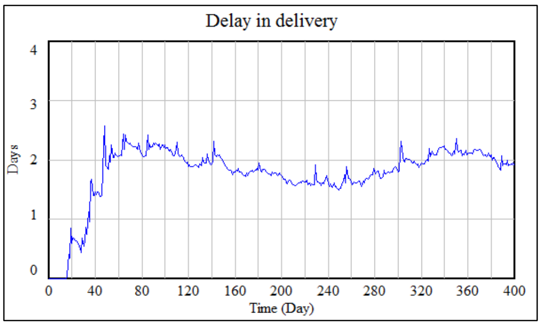
Manufacturing Delay risk – Fineblanking vs Grinding: Initially, the manufacturing delay risk likelihood, displayed in Figure 21(c), at both the fineblanking and the grinding stations is high. As this risk starts impacting the production line, risk response activities take place. Manufacturing delays are affected by procurement time delay, OEE factors related risk and new product testing. Risk response activities are directed towards reducing risk likelihood of OEE factors related risk. This is what brings down the manufacturing delay risk likelihood as time progresses. Risk response intends to drive the risk likelihood to a minimum value.

Manufacturing delay risk at fineblanking station is slightly higher when compared to that of grinding station. However, the impact of Grinding delays is much higher on the production line as it is the bottleneck operation.

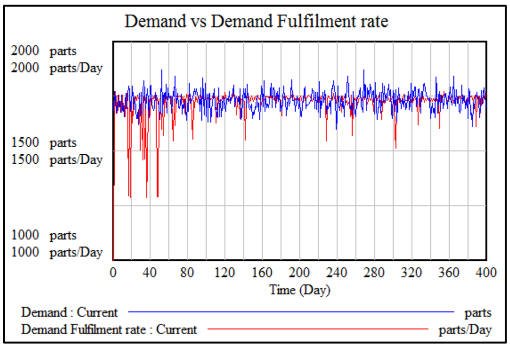
Fineblanking rate: Fineblanking station has a high production capacity. The actual throughput is quite low compared to its capacity as it depends on the demand. As shown in Figure 21(d), the effect of risk events at the fineblanking station is quite low on the production line because of the high production capacity. Initially risk events at the Fineblanking station occur frequently. The impact of these risk events is indicated in the form of delay in delivery performance indicator. Risk response activities take place actively causing a decline in risk occurrence.

Grinding rate: Grinding station is the bottleneck operation and has a huge impact on the production line when subject to risk events. As shown in Figure 21(e), the initial impact of risks at the grinding station decreases the grinding rate drastically. The grinding rate is at its lowest on the 33rd day at 1284 parts. The demand for the product is 1724 parts/day on an average and the low grinding rate leads to delay in delivery. As risk response activities take place, grinding rate is more stable. With the reduction in risk likelihood, risk impact also reduces. Towards the latter part of the simulation period, the grinding station is relatively stable with the lowest grinding rate on the 300th day at 1512 parts.

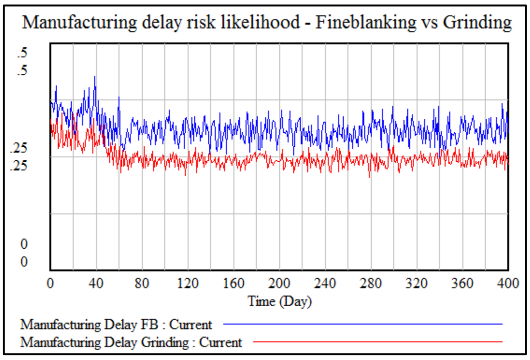
Revenue: From the Figure 21(f), revenue made from sales is quite high, around $10,200 per day initially. As the manufacturing delays start impacting delivery to the customer, a late delivery fee is imposed. This drives the revenue/day down. On 48th day, revenue/day is down to a low of $4773. With risk response activities reducing the impact of manufacturing delay risk events on the production line, there is an improvement in delivery and this is reflected in the revenue graph as well. Small fluctuations are observed in revenue/day from there on.



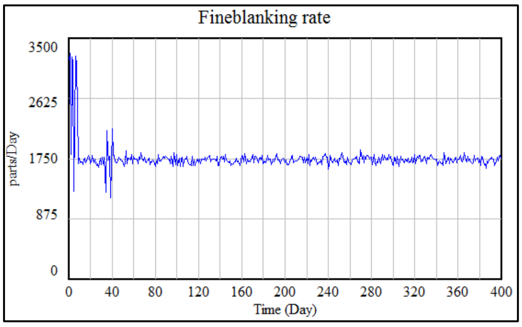
(a) Delay in delivery



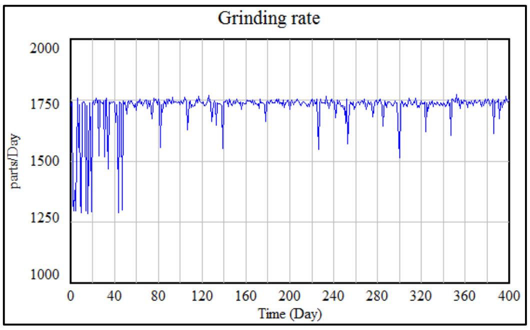
(b) Demand vs Demand fulfilment rate



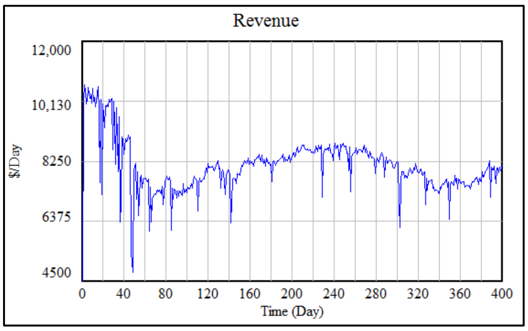
(c) Manufacturing delay risk likelihood.



(d) Fineblanking rate.



(e) Grinding rate



(f) Revenue

Figure 21: Key performance indicators for scenario 1.

Scenario 5:

Delay in Delivery: As shown in Figure 22(a), a high risk likelihood at the bottleneck station has a huge impact on the production line. A huge delay in delivery of 5.48 days is experienced on 50th day. The risk response activities help in reducing the delay in delivery. The high risk at bottleneck station drives the risk down aggressively.

However, the grinding station capacity is not enough to compensate for the delay in delivery caused during the beginning of the simulation time period. Hence, even after risk likelihood is reduced, there is only a marginal decrease in delay in delivery.

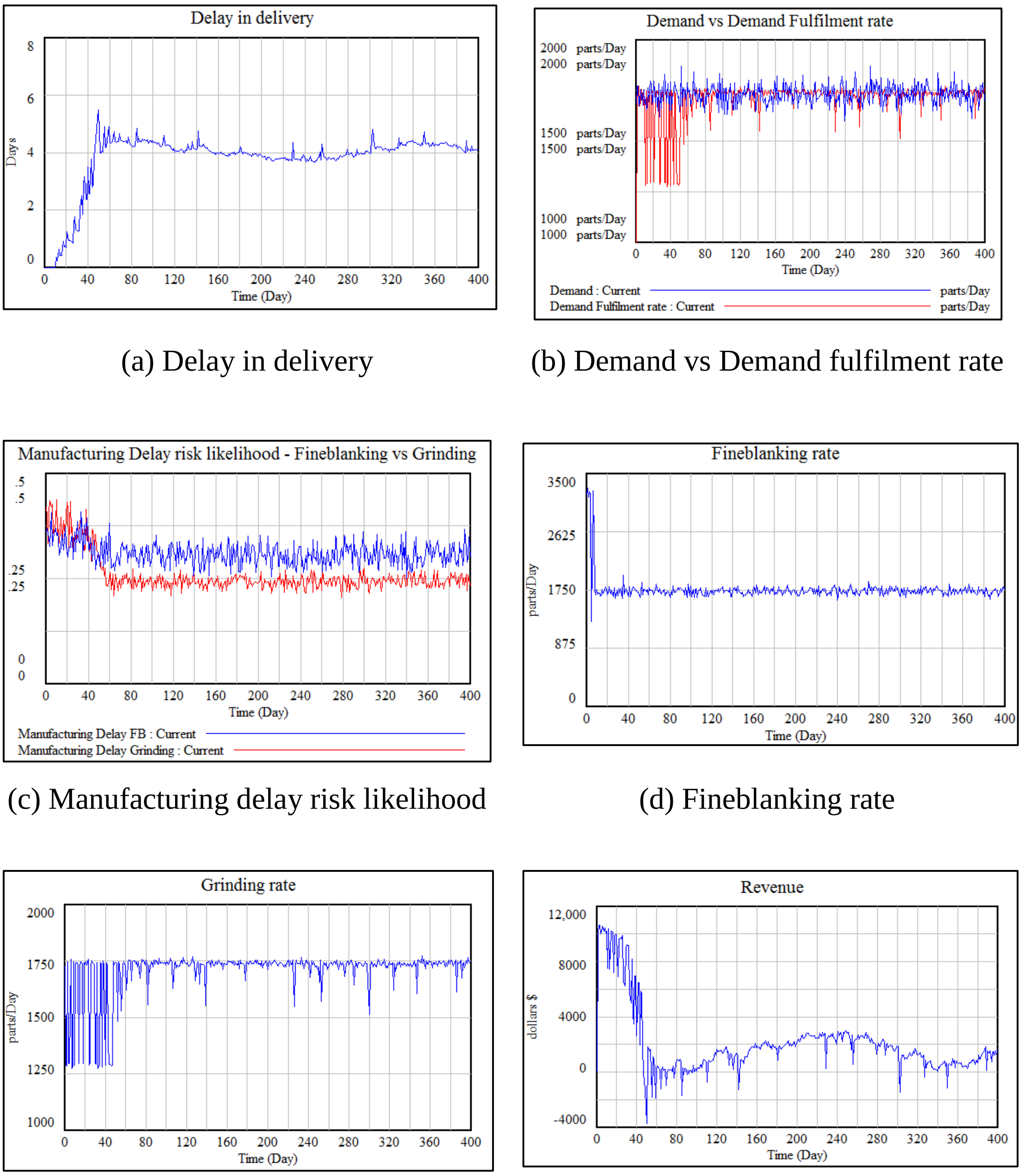
Demand vs Demand fulfilment rate: As seen in Figure 22(b), demand fulfilment rate is almost equal to the demand until risk events impact the production line. A severe drop to 1300 parts is seen in the demand fulfilment rate on the 82nd day. As risk response activities take place, demand fulfilment rate improves again.

Manufacturing delay risk – fineblanking vs grinding: It can be seen in Figure 22(c) that the likelihood of manufacturing delay risk is high initially. Around the 40th day risk response activities take place and reduces the likelihood of risk events.

Fineblanking rate: Fineblanking rate, as shown in Figure 22(d), is reduced to 1272 parts on 5th day. Due to the high production capacity at fineblanking station, loss in production is covered on the following day. With risk response activities taking place, there is no further impact on the fineblanking rate.

Grinding rate: Initially, manufacturing delay risk events have a huge impact on grinding rate as shown in Figure 22(e). On the 7th day production rate at Grinding station is the lowest at 1273 parts. With risk response activities taking place, the impact of risk events on grinding station becomes significantly lower.

Revenue: Revenue graph, from Figure 22(f), shows a steep decline due to the increase in delay in delivery and decrease in demand fulfilment rate. A loss of $3,711 is observed on 50th day. Revenue is on the negative side for 4 days. With risk response activities, demand fulfilment rate is restored to the normal rate. However, delay in delivery, which is difficult to compensate because of low grinding capacity, lead to huge losses. In conclusion, a high risk at grinding station leads to huge losses to the company.



(a) Delay in delivery

(b) Demand vs Demand fulfilment rate

(c) Manufacturing delay risk likelihood

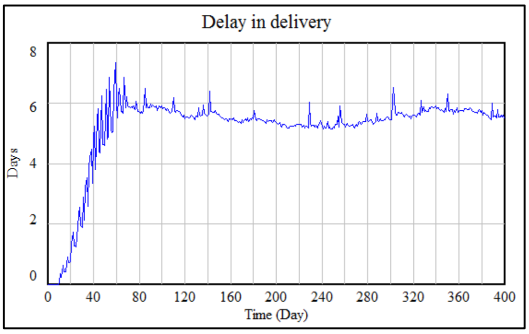
(d) Fineblanking rate

(e) Grinding rate.

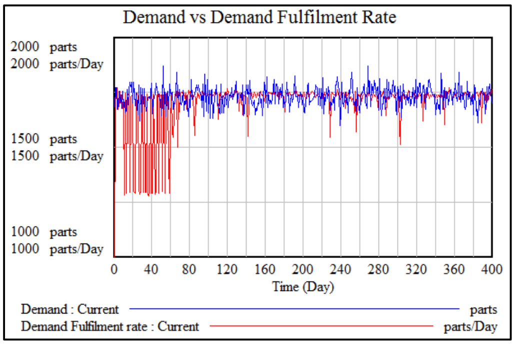
(f) Revenue

Figure 22: Key performance indicators for scenario 5.

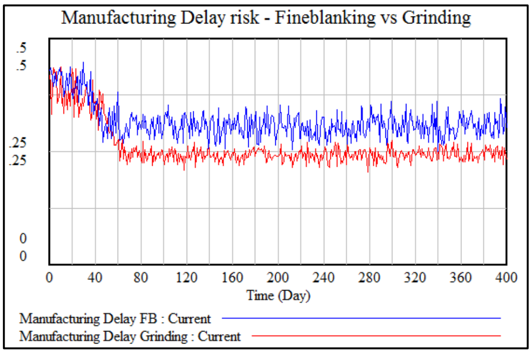
Scenario 10:



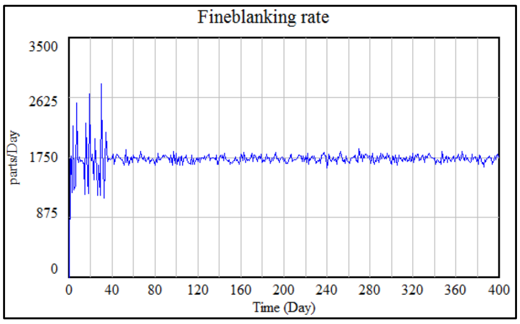
(a) Delay in delivery



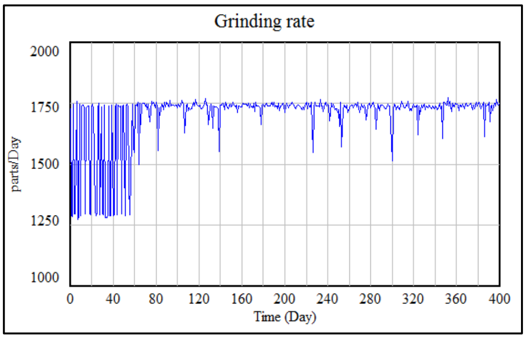
(b) Demand vs demand fulfilment rate



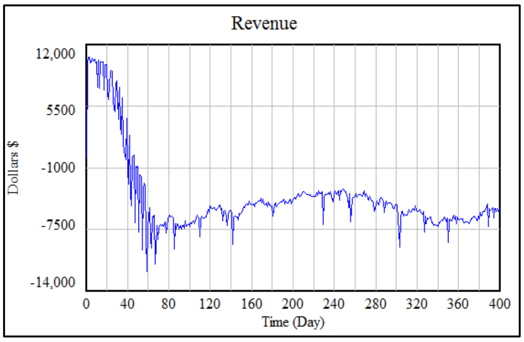
(c) Manufacturing delay risk



(d) Fineblanking rate



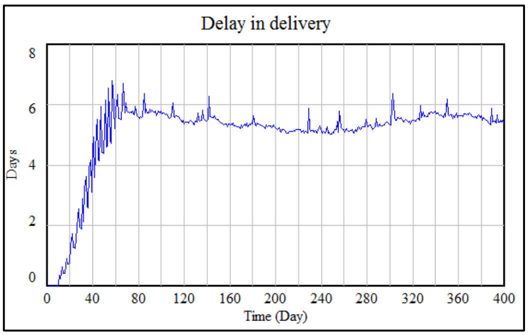
(e) Grinding rate



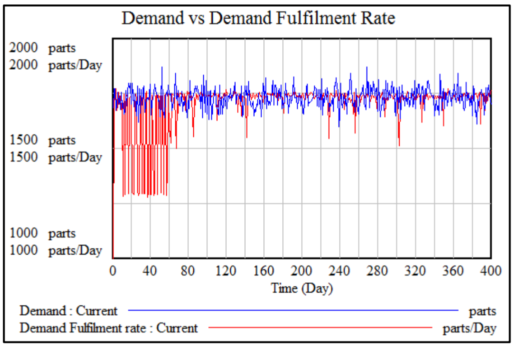
(f) Revenue

Figure 23: Key performance indicators for scenario 10.

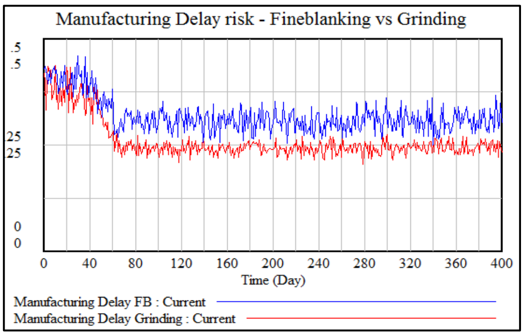
Scenario 11:



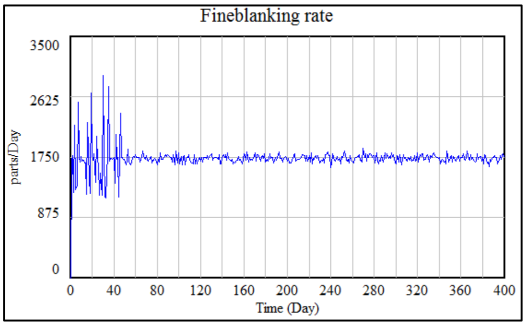
(a) Delay in Delivery



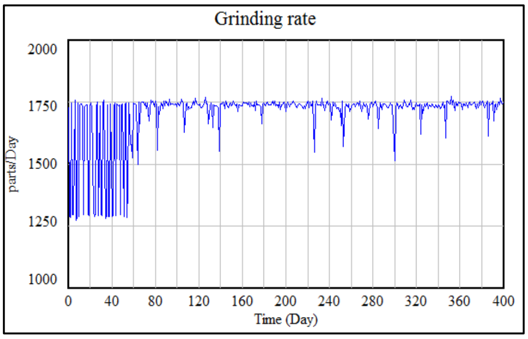
(b) Demand vs Demand fulfilment rate.



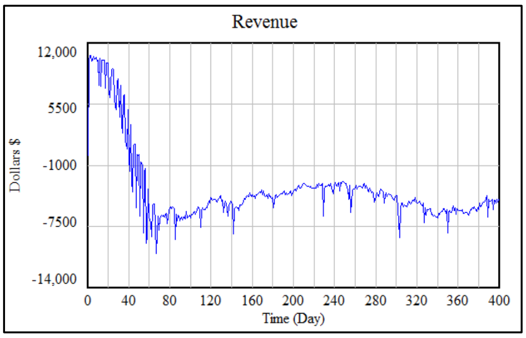
(c) Manufacturing delay risk



(d) Fineblanking rate



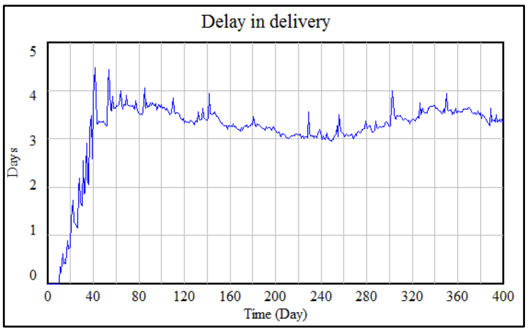
(e) Grinding rate



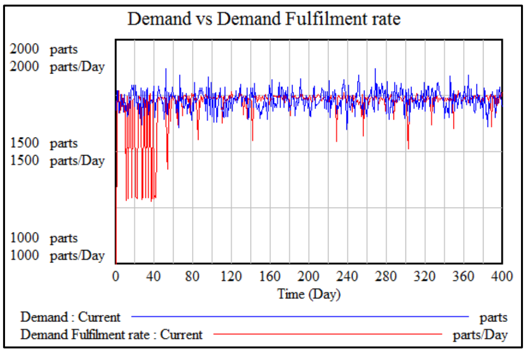
(f) Revenue

Figure 24: Key performance indicators for scenario 11.

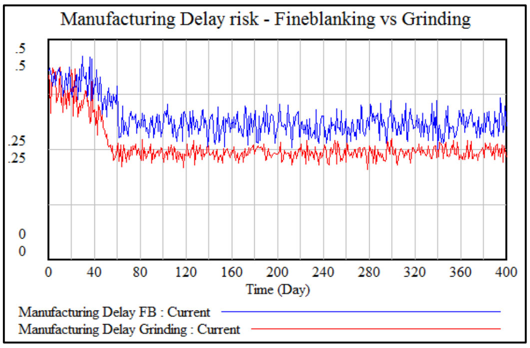
Scenario 16:



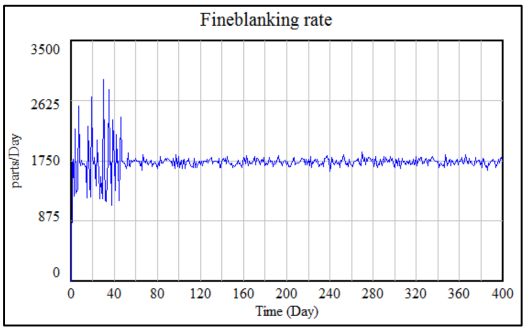
(a) Delay in delivery



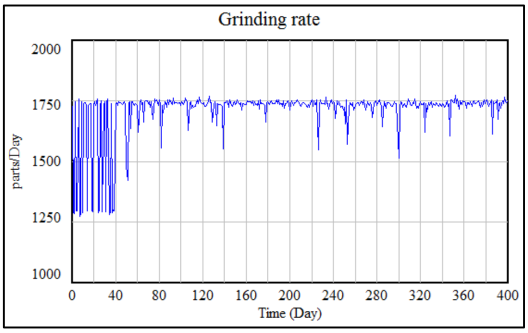
(b) Demand vs Demand Fulfilment rate.



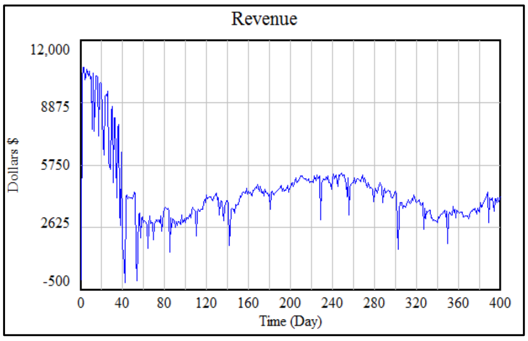
(c) Manufacturing delay risk



(d) Fineblanking rate.



(e) Grinding rate



(f) Revenue

Figure 25: Key performance indicators for scenario 16.

The results obtained through the combination of BBN risk model and SD production line model, aided in decision-making. Some of the key aspects in the behaviour of the system, which humans tend to misjudge, were captured through a mathematically well-structured risk assessment model.

The results obtained reflect the performance of the production line with the existing capacity. Almost all the delay in delivery is caused due to the high demand for the product. With a marginal difference in demand and production capacity at the bottleneck station, delay in delivery is bound to occur when a risk event impacts the production line. Also, most of the production delay that occurred during a risk event, continued until the end of the simulation period because the impact caused by risk events was hard to compensate for with the existing production capacity.

5.2.3 Effect of Overtime on Delay in Delivery

On the other hand, industry personnel have several quick action plans to deal with problems in meeting customer's demand. Order backlog is not allowed to continue for extended periods of time because that would hurt their profits and tarnish their reputation. Hence, to obtain further insight into the production line system behaviour, production line was customized as per requirement. Some of the quick action plans reviewed are:

1. **Overtime**: Increasing capacity by working extra hours is one of the easiest and a low risk alternative to meet the demand. However, it has its own share of problems. Working overtime can sometimes lead to a reduced operator efficiency. Also, overtime costs are high considering operator and engineer costs, electricity etc.
2. **Hiring temporary workers**: When the demand is high, production managers increase their workforce to match the demand. Temporary workers help boost the production capacity. Proper scheduling of jobs along with the extra workforce could help bridge the gap between demand and supply. However, the time required to train temporary workers might worsen the situation. Also,

finding skilled temporary workers is a tedious task and the paper work required makes it a less preferred quick response.

3. **Building high inventory**: Inventory is a liability which could prove to be an asset to the company, provided, it is monitored and managed properly. Building high inventory would increase storage costs tremendously as the material that the product is made out of is mild steel, which is prone to corrosion. Also, there is a limit to which inventory can be increased. This option is the least preferred one as a lot of money is tied up in the form of inventory.
4. **Accommodating delayed jobs on other machines:** Accommodating delayed jobs on other machines might prove to be a good temporary solution to the production capacity problem. However, it might not be possible to customize machines to run delayed jobs easily. Engineers might have to invest more time and money to design fixtures and optimize process parameters. Additionally, it might lead to a delay on other jobs. Hence, this option is certainly the last resort.

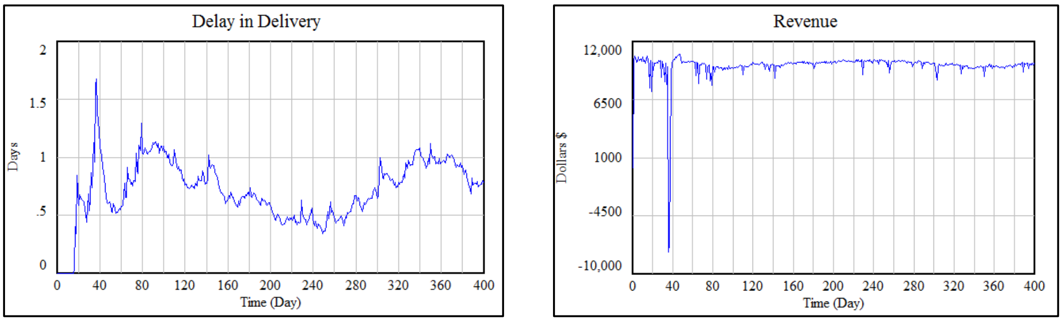
Increasing capacity through overtime is chosen as the most feasible option. Testing the production line under the increased capacity condition was important because it was not possible for the company to indulge in risk management activities every time a risk event occurs. Sometimes, industry personnel prefer to compensate for the loss in production by working extra hours. Also, behaviour of the production line was assessed by varying the mean demand and is recorded in the appendix section. Understanding the capabilities of the production line under different demand patterns would help managers, engineers and schedulers prepare contingency plans.

Labour and other operating costs per part calculated was based on the available data. 7.5 hours of extra time was considered per day, each shift working 3.75 hours extra. After an elaborate discussion, it was decided that excess capacity would be added when delay in delivery exceeds 1.5 days. This information was fed into the simulation model and simulated for 400 days.

Scenario 1:

Delay in delivery: Delay in delivery starts on the 16th day and increases to 1.62 days on the 36th day. Extra capacity is added as a result of this delay by increasing working hours. Risk response activities occuring simultaneously help in keeping the delivery delay to a low till the end of simulation period.

Revenue: On the 36th and 37th day, revenue/day drops down below -$7,000. It is on these days when excess capacity is added through overtime. However, the cumulative revenue generated at the end of the simulation period is $650,000 more.

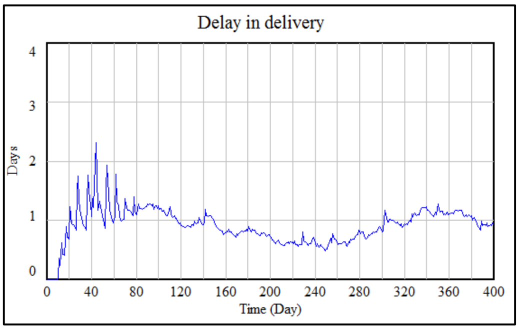


(a) Delay in delivery under overtime (b) Revenue under overtime

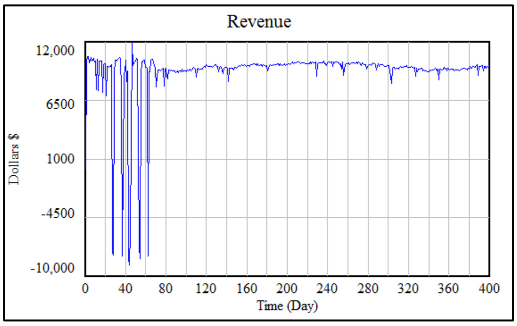
Figure 26: Effect of overtime on scenario 1

Scenario 5:

Cumulative revenue for 400 days is equal to $3.69 million, where as, the cumulative revenue is $829,542 without making use of extra capacity.



(a) Delay in delivery under overtime.

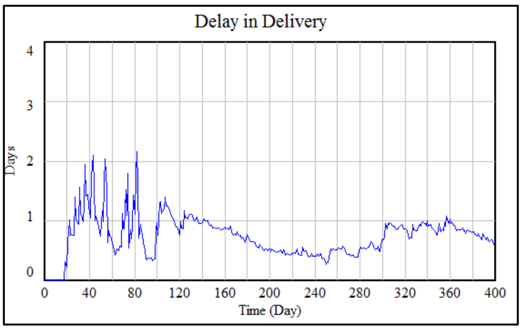


(b) Revenue under overtime

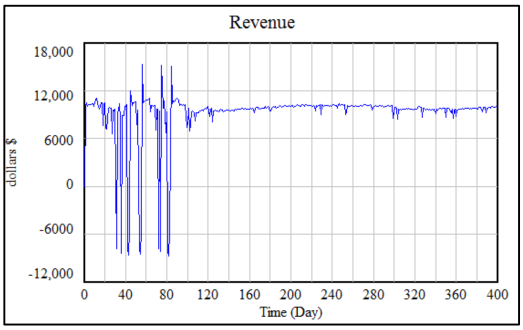
Figure 27: Effect of overtime on scenario 5.

Scenario 10

The cumulative revenue is $3.7 million when extra capacity is added through overtime. Cumulative revenue is at -$1.67 million dollars without making use of extra capacity.



(a) Delay in delivery under overtime.

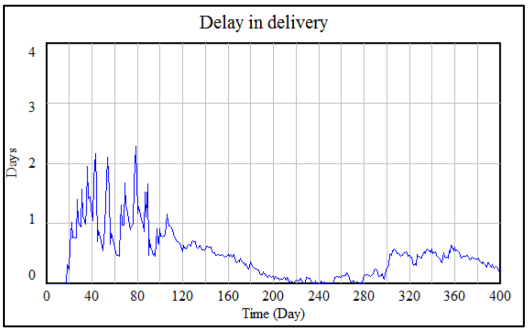


(b) Revenue under overtime.

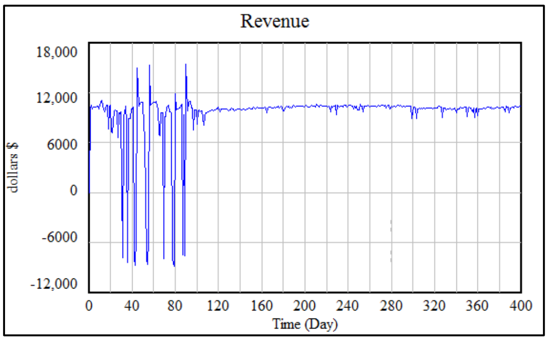
Figure 28: Effect of overtime on scenario 10.

Scenario 11:

The cumulative revenue is $3.719 million when extra capacity is added through overtime. Cumulative revenue is at -$1.4 million without making use of extra capacity through overtime.



(a) Delay in delivery under overtime.

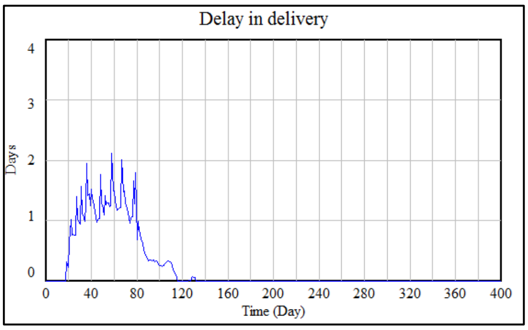


(b) Revenue under overtime.

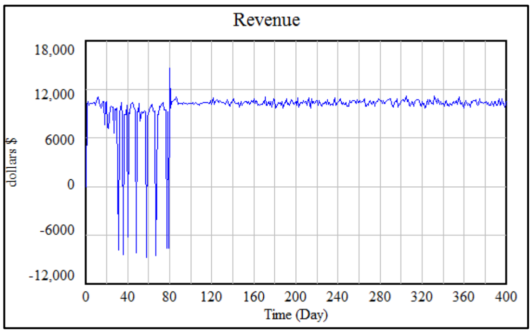
Figure 29: Effect of overtime on scenario 11.

Scenario 16:

The cumulative revenue is $3.936 million when extra capacity is added through overtime. Cumulative revenue is at $1.735 million when extra capacity isn't utilized.



(a) Delay in delivery under overtime.



(b) Revenue under overtime.

Figure 30: Effect of overtime on scenario 16.

6. Discussions and Conclusions

The proposed methodology provides a versatile technique to assess the impact of risks affecting the production line. The BBN model captures the relationships between risk events through the node probability tables and calculates the posterior probabilities of risk events. Integrating this BBN model with SD production line model and simulating the model helps understand the impact of these risk events on the performance of the production line. KPIs are monitored to examine the behavior of the system under the influence of risk events. The dynamic interaction between risk events and the production line is captured by using feedback loops from SD production line model to the BBN risk model, which is triggered by the KPIs. This BBN-integrated SD modelling bridges the research gaps identified and helps users comprehensively understand the risks affecting a company.

6.1 Research contributions

Most of the techniques currently used for risk assessment fail to quantify risks and, simultaneously, assess the impact of risk events on the system. Techniques like BBN, fault trees, event trees and bow-ties focus mainly on the likelihood of risk events and the causal relationship between them. Alternative techniques such as risk matrix approach lack the sophistication required to quantify risks in a complex inter-connected system. Most of these existing techniques fail to capture the transient effect of risks on the production line over a period of time and how the system will change. Although simulation techniques can be used to model the transient behaviour of a production line, they alone cannot capture sudden changes/disruptions in the production line caused by the risk events.

This research presented a comprehensive risk assessment methodology to quantify risks affecting the production line and study the transient impact of these risks on the production line. Integrating BBN with SD simulation model provides the simulation technique with a complementary capability to capture the causal relationships between risks and to quantify them. This results in a versatile technique to assess production line under the influence of risk events.

6.2 Industry Relevance

Company-wide risk assessment is still in its nascent stages despite its importance being acknowledged by many practitioners and academicians. Risk management in industries is mostly confined to occupational safety and disaster management. Few industries that recognize the impact of risks on their global supply chain invest their time and money on supply chain risk management. However, risks impacting the internal operations/ production line are often neglected. This is largely due to the lack of knowledge on the operational risks and the effect of these risks on the internal operations. Engineers and managers at the middle management level are aware of some of the frequently occurring risk events but do not understand the full extent to which these risks can affect the internal operations/production line.

Research focussed on operational risks at the production line level, helped gain some insights that would benefit industries. The methodology allows industry personnel to amalgamate real-time data and expert opinion/perception to assess the performance of the production line. It allows them to contemplate the future by simulating the model and by evaluating multiple key metrics. Risk assessment is followed by decision-making which is one of the key elements where the industry personnel desire tools to support them. Analyzing several scenarios by adding, removing and/or changing system variables helps individuals to visualize their decisions and their consequences. Using such a tool improves the production line utilization, resource allocation, labour assignments, profitability and product delivery, ultimately leading to customer satisfaction.

Production and management personnel are aware of the importance of risk management for operations reliability. They, generally, have an idea about some of the risks impacting internal operations, however, the full extent of the impact of risks on the production line is not known to them. Insights gained from this research suggest that it is the interaction between production line and the risks that determines the overall performance of the production line. A high risk might not necessarily result in a huge impact on KPIs and vice-versa. The system/production line has an intrinsic capability to deal with the impact of risk events up to a certain extent. Hence, from a broader perspective, it would be highly beneficial for industry personnel to understand this interaction between risk events and production line to prioritize risks for mitigation strategies.

6.3 Challenges

During the initial phase of research, one of the biggest challenges was to find the simulation platform that would enable BBN risk and SD production line modelling. Vensim was chosen as it enabled to accomplish the task and was an open-source software. Vensim is capable of modelling both discrete and continuous variables. Discrete variables in the production line were modelled using discrete functions like delays and integer constraints. Some other constraints had to be added to make it relevant for production line modelling. For example, WIP at different stations, which were modelled as stocks, could assume either positive or negative real number. To prevent this error, non-negative constraints were added to the WIP quantities and functions were introduced to make production rate to be zero when the WIP quantity was zero.

Another concern was in the estimation of severity of the child risk event on the production line variable with which it directly interacts. Since the scope of risk assessment was at the production line level, proportionality between likelihood and severity of risk events was assumed. Additionally, a function was required to capture the interaction between production line variables, risk likelihood and risk severity. PULSETRAIN, a Vensim in-built function, was eventually chosen to model the impact of risk events on the production line variable.

6.4 Limitations

Although the BBN-integrated SD model is a versatile technique for risk assessment, it has some limitations that are important to note. One of the most tedious and time consuming task is to define system boundaries and variables to be modelled, especially for first time users. Additionally, users need to have a decent understanding of the mathematics behind BBN as they would need to manually construct the BBN risk model within Vensim. Also, users must be capable of debugging the model by adding/removing constraints or making changes to the functions in order to incorporate the complexity within a system.

6.5 Future work

Future work would be focussed on overcoming some of the limitations in the model. One of the major tasks is to facilitate the process of modelling. The interface would be made more user-friendly by developing the model within excel and transferring data to Vensim. Excel would allow for a much easier and familiar approach where each cell in the excel spreadsheet can be represented as a variable and any changes to the model (such as adding variables, changing prior probabilities etc.) can be easily performed in the excel file. These changes would then be reflected in the SD model when data is transferred. Similarly, results of the production line KPIs could be exported to excel for further data analysis. Excel VBA could be an effective way of creating a user-friendly interface that would encourage more users to make utilize the risk assessment model.

Additionally, back propagation capability would be introduced to the model. Back propagation is one of the key features of BBN, which helps calculate the likelihood of parent nodes based on the likelihood of child node, thus identifying the root causes. This property would provide industry personnel to identify root causes of risk events and thus manage the production line better.

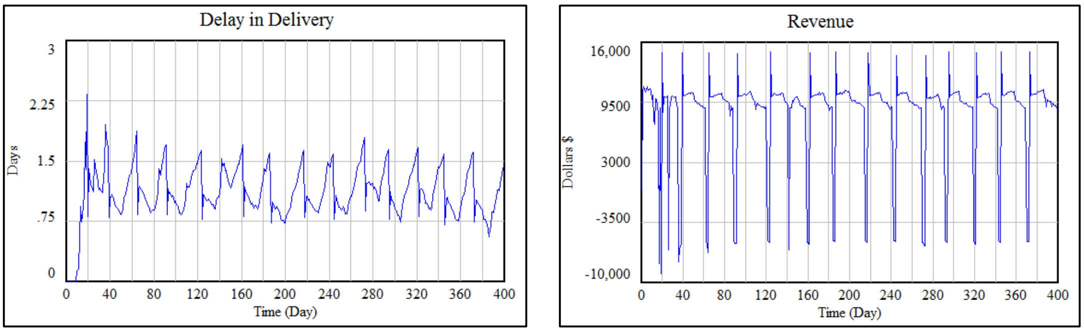
Appendix: Effect of Overtime and Varying Demand on Scenarios

Scenario 1

(1) Under high demand of 1825 parts/day (mean)

Delay in Delivery: Delivery delays start on the 10th day and exceeds 1.5 days in delay for a total of 43 times. Extra capacity is added as a result of this delay by increasing working hours. Risk response activities occuring simultaneously help in reducing delivery delays. However, due to the high demand, delivery delays are bound to occur.

Revenue: Overtime is triggered 43 times throughout the simulation period. Overtime cost is about $14,000. This causes huge losses when overtime is triggered. The cumulative revenue using extra capacity is $3.18 M, compared to -$31M loss without the extra capacity.



(a) Delay in delivery under overtime (b) Revenue under overtime.

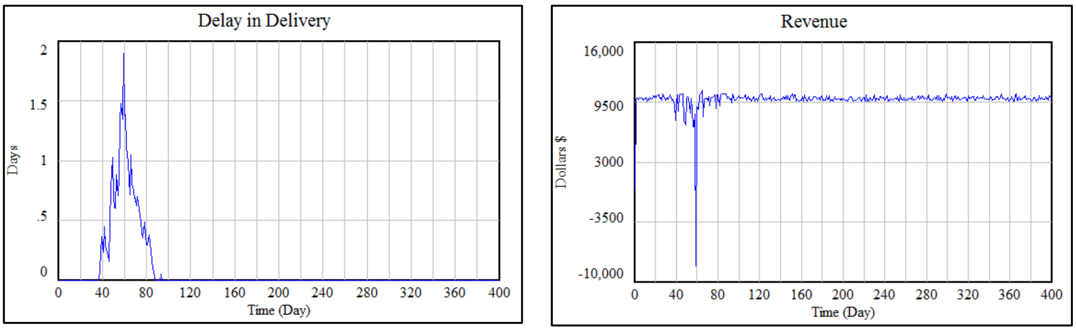
Figure 31: Effect of overtime on scenario 1 when demand is high.

(2) Low demand = 1620 parts/day

Delay in Delivery: Delivery delays start on the 38th day. Overtime is triggered on 59th day. Extra capacity and risk management activities occuring simultaneously reduce delivery delays.

Revenue: Overtime is triggered on 59th day. Cumulative revenue is $11,000 less.

Hence, it can be concluded that during a low demand it is better to engage in risk management rather than working overtime.

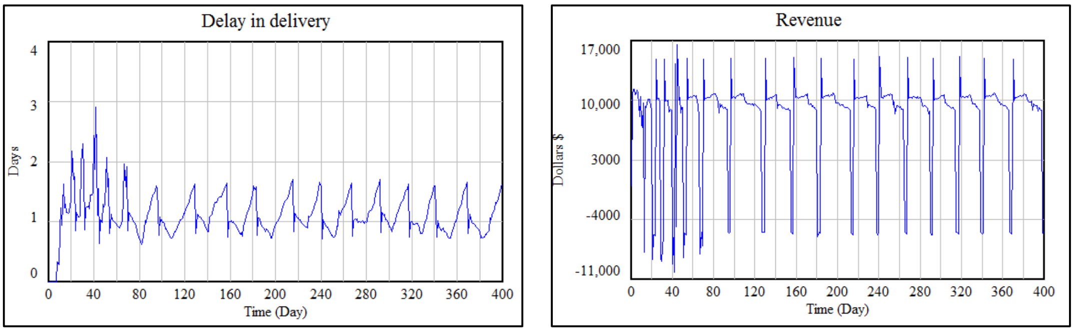


(a) Delay in delivery under overtime. (b) Revenue under overtime.

Figure 32: Effect of overtime on scenario 1 when demand is low.

Scenario 5

(1) Under high demand of 1825 parts/day (mean).

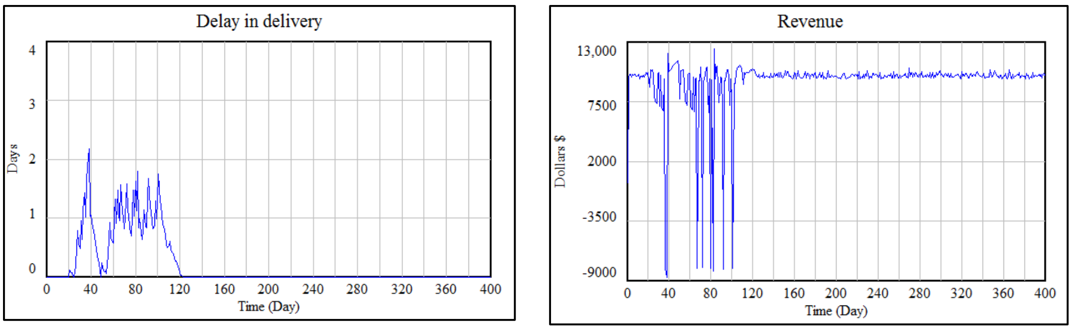


(a) Delay in delivery under overtime. (b) Revenue under overtime.

Figure 33: Effect of overtime on scenario 5 under high demand.

(2) Under low demand of 1620 parts/day (mean).

The cumulative revenue is $25,000 higher than the case without using extra capacity.



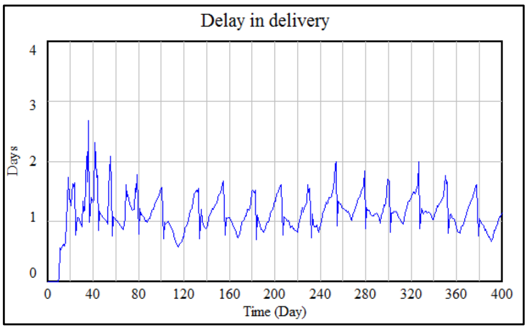
(a) Delay in delivery under overtime. (b) Revenue under overtime.

Figure 34: Effect of overtime on scenario 5 when demand is low.

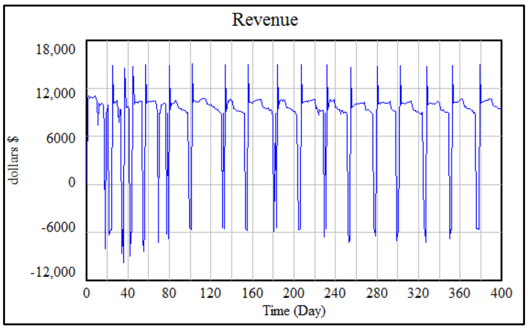
Scenario 16

(1) Under high demand of 1825 parts/day (mean).

The cumulative revenue is $3.218 million when extra capacity is added through overtime.



(a) Delay in delivery under overtime.

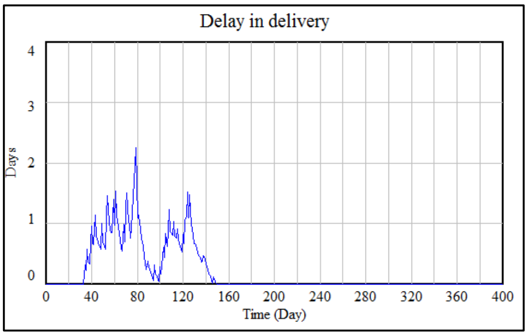


(b) Revenue under overtime.

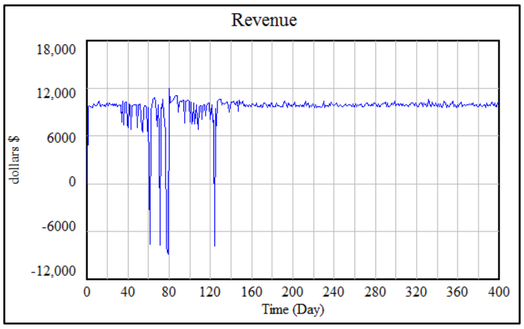
Figure 35: Effect of overtime on scenario 16 when demand is high.

(2) Low demand = 1620 parts/day

The cumulative revenue is $3.218 million when extra capacity is added through overtime.



(a) Delay in delivery under overtime.



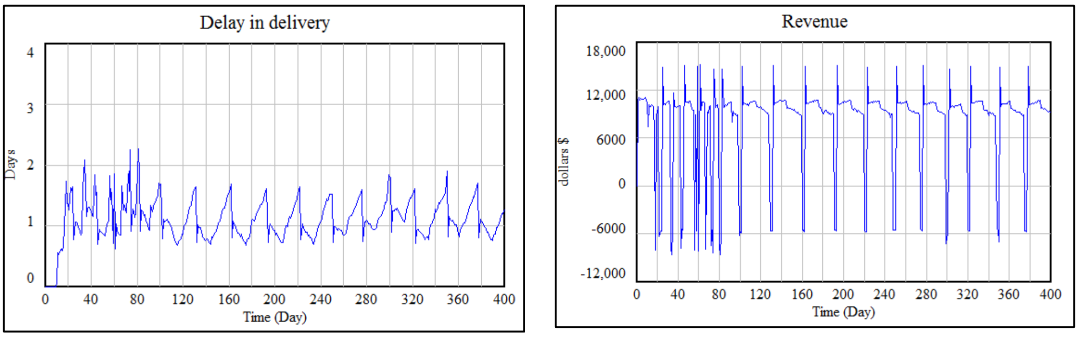
(a) Revenue under overtime.

Figure 36: Effect of overtime on scenario 16 when demand is low.

Scenario 11

(1) Under high demand of 1825 parts/day (mean).

The cumulative revenue is $3.17 million when extra capacity is added through overtime.

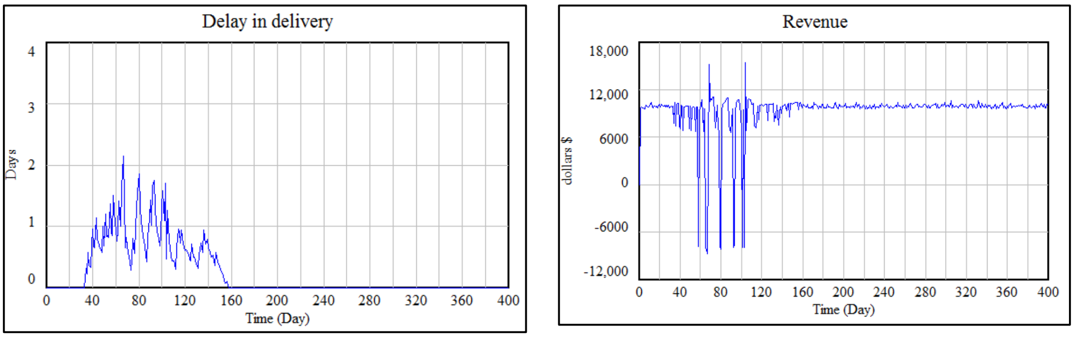


(a) Delay in delivery under overtime. (b) Revenue under overtime.

Figure 37: Effect of overtime on scenario 11 when demand is high.

(2) Under low demand of 1620 parts/day (mean).

The cumulative revenue is $3.73 million when extra capacity is added through overtime.



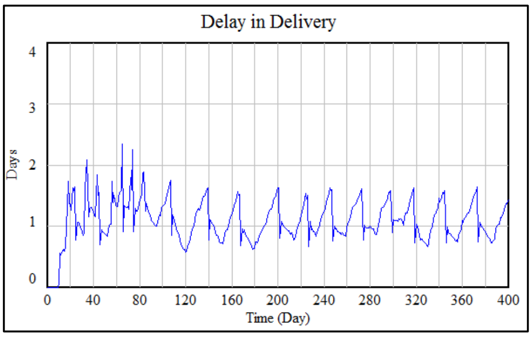
(a) Delay in delivery under overtime. (b) Revenue under overtime.

Figure 38: Effect of overtime on scenario 11 when demand is low.

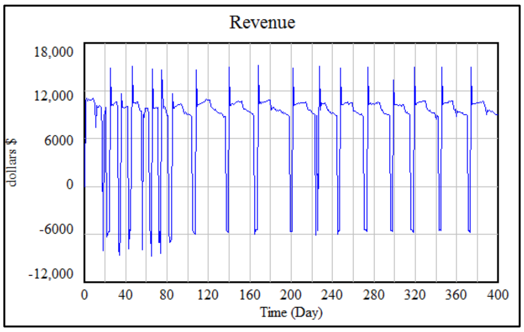
Scenario 10

(1) Under high demand of 1825 parts/day (mean).

Cumulative revenue is $3.18 million in this case.



(a) Delay in delivery under overtime.

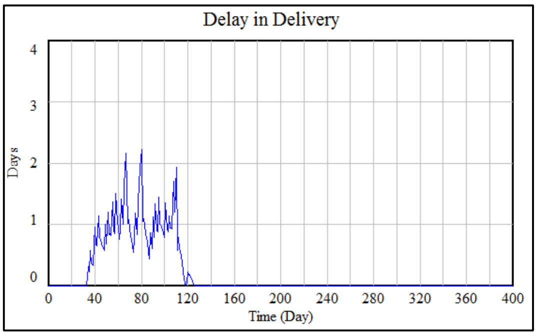


(b) Revenue under overtime.

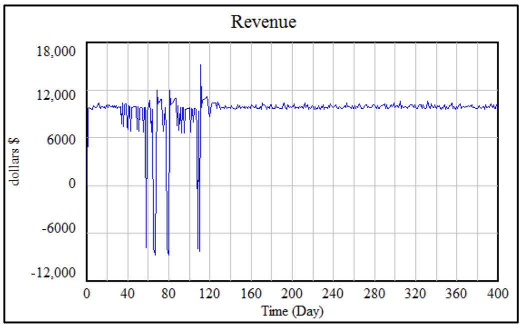
Figure 39: Effect of overtime on scenario 10 when demand is high.

(2) Under a low demand of 1620 parts/day (mean).

The cumulative revenue is $3.75 million when extra capacity is added through overtime.



(a) Delay in delivery under overtime.



(b) Revenue under overtime.

Figure 40: Effect of overtime on scenario 10 when demand is low.

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