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Assessing Production Line Risk using Bayesian Belief Networks and System Dynamics

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Abstract

Increased complexity in product design, strict regulations and a changing market make risk assessment critical for successful operations. Failure in responding quickly to raw material shortages, downtimes, deteriorating equipment conditions or other operational issues can prove to be an expensive affair. A company-wide risk assessment includes both external and internal operations. However, external/supplier risk assessment has been of major interest. Even though the scope of risk assessment at the production line level is not as broad as it is at the supply chain level, assessing risk would help recognize vulnerable areas of the production line, which would in turn help reduce damage caused when risk events occur. In this research, a method for production line risk assessment is proposed by considering operational risks affecting the line. Operational risks and their causal relationships are represented using Bayesian Belief Networks (BBN). The impact of these risks is observed using a simulation model of the production line using System Dynamics (SD) approach. The combination of BBN and SD assists in developing a versatile methodology, which can capture the dynamic causal mechanisms in a complex system, the uncertainties amongst risk events and the long-term impact of operational risks on the production line.

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Keywords: Risk Assessment; Bayesian Belief Networks; System Dynamics.

1. Introduction

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. Moreover, companies are willing to take some extra risk to survive and succeed in an increasingly competitive market. Often, production capacities and capabilities are quoted aggressively in order to get the job. Under

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such circumstances, failure to respond quickly to raw material shortages, downtimes, deteriorating equipment conditions or other operational risks could prove to be an expensive affair. This makes a company-wide risk assessment of critical value. Such a practice gives a holistic view of the risks affecting a company and provides opportunities to mitigate them. In addition, ISO 31000 encourages companies to adopt risk-based decision-making and requires them to develop a 'Risk Profile' [1].

The scope of a company-wide risk assessment includes both internal and external operations. However, external/supplier risk assessment has drawn overwhelming attention compared to internal/production line risk assessment. William et. al [2] identified this trend when only 3 research studies regarding manufacturing 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, it is still of significant importance as it would give a company an edge over its competitors, within the industry, by ensuring financial strength, quality of goods and services and customer satisfaction. Therefore, objectives of the research presented in this paper 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.

The remainder of the paper is organized as follows. Section 2 presents a brief summary of the literature review and identifies gaps in research. Section 3 provides details on the Production Line Risk Assessment (PLRA) methodology developed by combining Bayesian Belief Networks (BBN) and System Dynamics (SD). The application of methodology to a production line case study is also presented in this section. Results and discussion are presented in Section 4 where the effectiveness of the methodology in assessing the behavior of the production line system is examined. A summary of the paper and future work is described in the conclusions section.

2. Literature review

Since production line risk assessment is a less explored field, published literature in supply chain risk assessment was also reviewed. Quantitative risk assessment was the prime focus of the research. Bustad & Bayer [3] presented a risk management process at Coca Cola Enterprises through the Hazard and Operability (HAZOP) method. They identified risks impacting the industry and these risks were assessed using risk-appetite matrix. This approach is good for creating awareness and could work as a quick overview of the risks impacting the production line. However, the HAZOP method is mostly qualitative and cannot account for the uncertainty due to the complexity in the system.

Alternatively, the Fault Tree approach of assessing the reliability of the production line was demonstrated in [4, 5]. This approach gives an insight into the events resulting in a failure event. However, it is deterministic and does not capture the interdependencies between the risk events, as it depends on logical operators.

Bayesian Belief Networks (BBN) is a good tool to calculate the likelihood of the risk events as it captures both the interdependencies between risk events and uncertainty in likelihood. Unlike fault trees, BBN make use of Node Probability Tables (NPT), which capture the complex inter-dependent relationships between events in an efficient manner. 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 & Sou [6], supply chain risk analysis using BBN was demonstrated by Badurdeen et. al [7] and additional case studies were presented in Amundson et. al [8]. Badurdeen et. al [7] outlined a well-structured method for Supply Chain Risk Assessment (SCRA) by linking the risk drivers to the performance measures. This model captures the uncertainty within the system in an effective way. However, risk events are not static in nature. Risk events evolve with time and the BBN models, when applied to a static data set, fail to capture this dynamic behavior. Thus, BBN models alone may not be able to capture the impact of these risk events over a period.

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. 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 & Mehrjerdi [9] to study the impact of risk events on performance metrics like sales, production, government support and raw materials. Similarly, a risk management process in NASA's shuttle launching system was studied by Dulac et. al [10] to capture the dynamic nature of risk and its 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 probabilistic exposure to risk events and transient impact over time. Mohaghegh [11] demonstrated the combination of SD and BBN for Socio-Technical Risk analysis. 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.

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.

3. Methodology

ISO 31000:2015 [1] defines Risk Assessment as a 3-step process:

(1) Risk Identification
(2) Risk Analysis
(3) Risk Evaluation

The methodology followed for each of these steps for this research is described in the sections below.

3.1 Risk Identification

Identifying risks is one of the most crucial steps for risk assessment. Badurdeen et. al [7] presented a comprehensive supply chain risk taxonomy. In their work, the 'Organizational risks' cluster includes several risks impacting the organization and the 'Operating risks' sub-cluster consists of risks relevant at the production line level. These risks, listed in the risk taxonomy, may or may not impact a specific production line but they serve as a guide during the risk identification phase.

Alternatively, conventional techniques like brainstorming, questionnaires, incident investigation, auditing and inspection and HAZOP (Hazard and Operability Studies) could be used for risk identification.

The influence of these risk events is assessed by studying how they affect variation of Key Performance Indicator (KPI). KPIs describe the overall performance of the production line succinctly. Analysing KPI graphs helps understand the behaviour of the system and allow management to take further action.

3.2 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 used to develop a more versatile tool for risk analysis.

Pearl [12] defines BBNs as directed acyclic graph, which consist of nodes/variables and arcs connecting dependent nodes. These relationships amongst nodes are defined through conditional probabilities.

BBNs are fundamentally based on the Bayes' theorem that can be stated as follows:

$$P(Pt \mid C) = \frac{P(C \mid Pt) * P(Pt)}{P(C)} \tag{1}$$

where, $P(Pt \mid C)$ is the conditional probability of occurrence of parent node (Pt) given that child node (C) occurs. Alternatively, $P(C \mid Pt)$ 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 Fig. 1. This table defines relationship between the child node and its parent nodes using conditional probabilities.

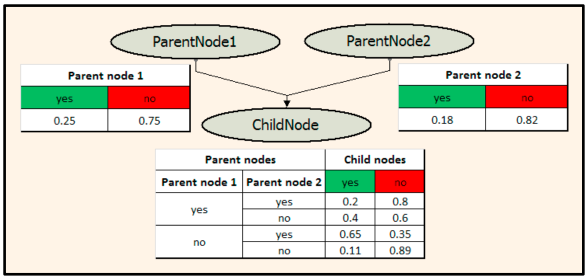


Fig 1: Node Probability Table -BBN

Fig. 2 shows the representation of BBN risk model in SD. Parent risk event 1 (RE1) and risk event 2 (RE2) are connected to child risk event 3 (RE3) using arcs. Likelihood of each risk event and their conditional probabilities are represented as a variable.

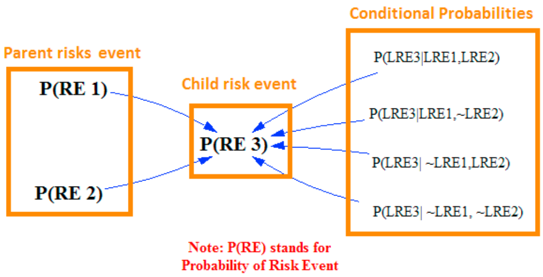


Fig. 2: Representing BBN in System Dynamics.

For the child nodes, 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 below:

$$\begin{aligned} P(RE3) &= (P(RE3) \mid RE1, RE2) * P(RE1) * P(RE2)) \\ &+ (P(RE3) \mid \sim RE1, \sim RE2) * (1 - P(RE1)) * (1 - P(RE2))) \\ &+ (P(RE3) \mid \sim RE1, RE2) * (1 - P(RE1)) * P(RE2)) \\ &+ (P(RE3) \mid RE1, \sim RE2) * P(RE1) * (1 - P(RE2))) \end{aligned} \quad (2)$$

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 [13] demonstrates an effective method to the construction and analysis of a Lean manufacturing system using SD. This method could be used in construction of production line model. Fig.3 depicts a production line model consisting of three workstations through which raw material gets processed. Raw materials and work in process (WIP) at each station are represented as stocks. Procurement rate and production rates at each station are flows that control the quantity of stocks. 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 child risk event, severity of risk event is calculated. Likelihood is the probability of occurrence of risk and severity is the severity of this risk in terms of loss in performance or resources. We assume proportionality 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 with 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, severity of risk event 3 is 200 parts. Similarly, when *P(RE3)* is between 0.2-0.3 then severity of risk event 3 is 250 parts. 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 (3) shows the calculation of risk event impact using the "*PULSETRAIN*", an in-built Vensim function that relates the impact frequency (1/*P(RE)*) and severity of risk event:

$$\begin{gathered} Risk\_event\_impact = \\ PULSETRAIN(impact\_start\_time, \\ impact\_duration, impact\_frequency, \\ final\_time) * Severity\_of\_risk\_event. \end{gathered} \quad (3)$$

PULSE is a Vensim function that returns 1 starting at time start and lasting for interval width. Equation 4 describes the math behind PULSE function.

$$\begin{gathered} If\_then\_else((start\_time + \mathrm{int}\,erval\_width) \\ > time > start\_time, 1, 0) \end{gathered} \quad (4)$$

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. In the example, RE3 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 5 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.

$$P(RE2) = P(RE2) * (1 - P(RM)) \\ + (\mathrm{Re}sidual\_risk * P(RM)) \tag{5}$$

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

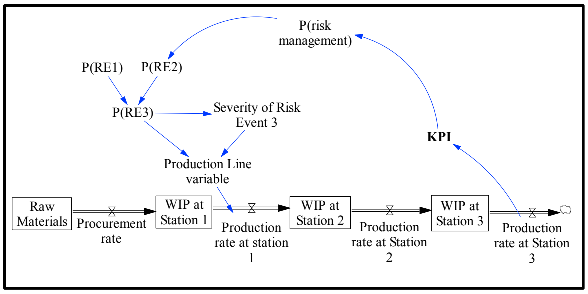


Fig. 3: Interaction between BBN and SD model.

3.3 Risk Evaluation

The impact of 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. Case Study

The automotive industry is one of the most competitive and risky industries in the manufacturing sector. Here, we use a case study from the automotive industry to demonstrate the application of the proposed method.

A growing supplier of precision metal components and assemblies using fineblanking technology was considered for risk assessment. The company operates at several locations across the globe including USA, Canada, Mexico and China.

One of the divisions in USA specializes in producing several kinds of engine plates and transmission parts, which are supplied to major automobile manufacturers. The company name and other information is withheld due to confidentiality reasons. One of the major and strategically important customer's products, Engine Plates, were selected for this application. Data regarding the process routing and production capacities were acquired using internal company database.

The process routing for producing engine plates, is as follows:

1. Fineblanking operation at 1600-ton press. (Production capacity: 3000 - 3750 parts/day)
2. Drilling station. (Production capacity: 2520 - 2700 parts/day)
3. Tapping and Countersink station. (Production capacity: 2380 - 2550 part/day)
4. Grinding operation. (Production capacity: 1680 - 1800 parts/day)
5. Belt-sand and Brush Operation. (Production capacity: 7000 - 7500 parts/day)
6. Inspection and Packing operations. (Production capacity: 1850 - 2025 parts/day)
7. Shipping (Capacity: 5500 parts/day)

4.1 Case Study- 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 [7] were referred during this phase.

Manufacturing disruptions or delays are the primary risks impacting production line. New product testing (NPT), procurement time delays (PTD) and OEE factors related risks (OEE) are the major risk events leading to the manufacturing delay (MD) risk. Raw material shortages (RMS), caused by poor supplier relationship (PSR), and delivery problems (DP) are the major risk events leading to procurement time delay (PTD) risk event.

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

4.2 Case Study - Risk Assessment

Vensim, an SD software, was used to develop the BBN and production line models.

Causal Loop Diagram (CLD) is an effective method for defining system variables and boundaries. CLD represents the cause & effect relationship between system variables, which acts as a useful tool while developing the Stock & Flow model. Fig.4 shows a CLD of the case study. Cause-effect relationship between risk events from BBN model and production line variables from production line SD model are represented.

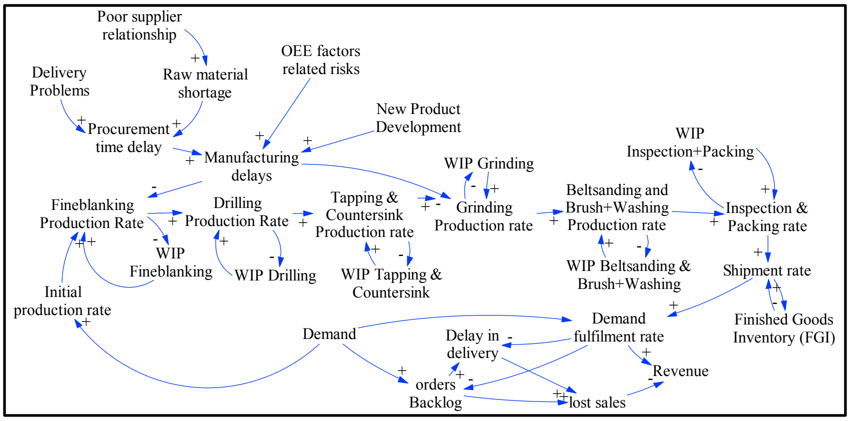


Fig. 4: Causal loop diagram- Case study

Based on CLD, BBN and production line SD models are developed.

BBN model consists of risks identified in step1. The likelihood of independent risk events and causal relationships between risk events is represented in Fig. 5. Conditional probabilities of each risk event are connected using an expression based on equation (2).

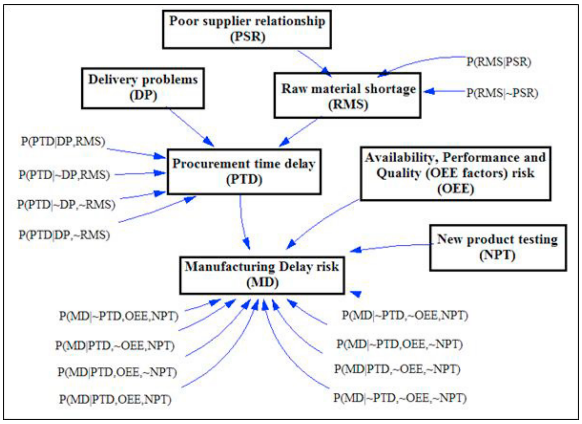


Fig.5: BBN risk model – Case study.

Fig.6 displays the prior probabilities fed into the BBN risk model. Data required to construct these tables were obtained by utilizing resources within the company (managers).

Poor supplier relationship	
Yes	No
0.2	0.8

New Product Testing	
Yes	No
0.38	0.62

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

Parent nodes		Procurement time delay	
Raw material shortage	Delivery problems	Yes	No
Yes	Yes	0.72	0.28
	No	0.65	0.35
No	Yes	0.6	0.4
	No	0.1	0.9

Parent nodes			Manufacturing delay	
Procurement time delay	New Product Testing	OEE factors risk	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

Delivery problems : Normal dist.- Min:0.2, Max:0.6, Mean: 0.4, Std. dev:0.05

OEE risk : Normal dist.- Min:0.4, Max:0.65, Mean: 0.5, Std. dev:0.15

Fig.6: Prior probabilities-BBN risk model

This is followed by developing the SD production line model as shown in Fig. 7. Each workstation 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, varying between the limits mentioned in the process routing, 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, were included. Actual production rate at each station depends on the minimum of WIP quantity at the station and capable production rate (production capacity). Work-In-Progress (WIP) at each station is computed based on the difference between entry and exit production rates at that station.

Inspection and packing station involves quality check. Defective products are reworked and introduced back to the production line. Defects percentage was obtained through the quality reports at the inspection station.

Demand follows a Normal distribution 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 the difference between revenue made from sales and lost sales.

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.

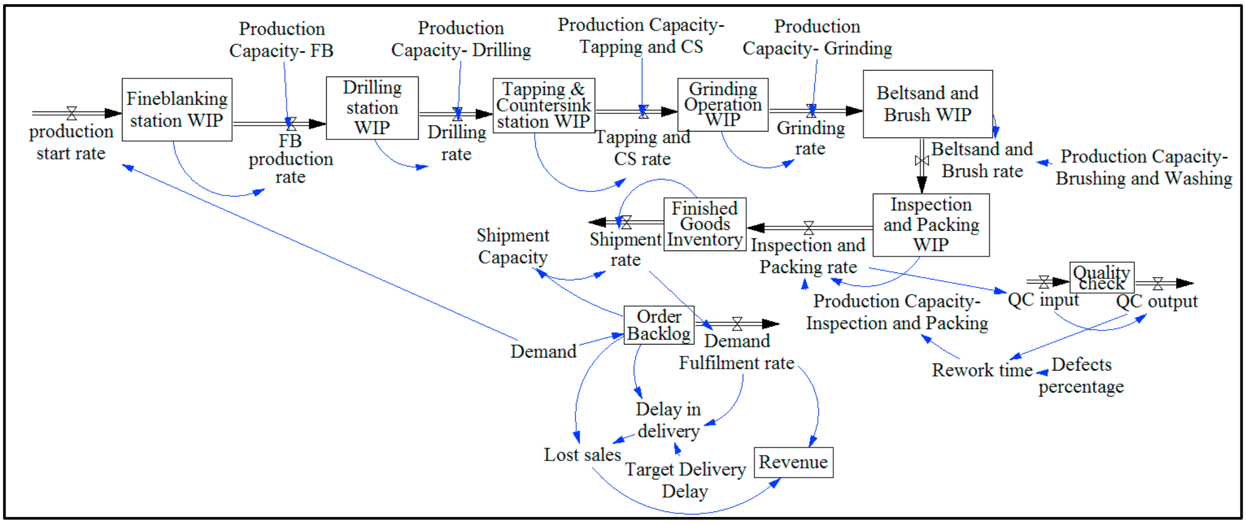


Fig.7: Production line SD model – Case study

The baseline production model was then connected to the BBN model for risk assessment as shown in Fig. 8. Manufacturing delay risk likelihoods (fineblanking and grinding), calculated from BBN model, forms the basis for impact frequency at the fineblanking and grinding stations. Severity of risk events were estimated with the help of industry personnel. Since the scope of risk assessment is at the production line level, proportionality is estimated between severity of risk events and risk likelihood.

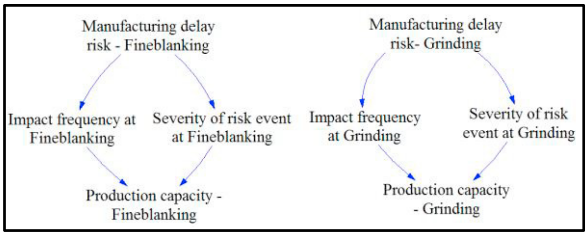


Fig.8: Interaction between BBN and SD model – Case Study

The dynamic nature of risk events is captured through risk management variable as shown in Fig. 9. Risk management likelihood depends on the delay in delivery. A proportional relationship is defined between risk management and "Delay in delivery" performance indicator. This risk management variable mitigates or reduces the likelihood of OEE factors related risks using equation 4. The model is then simulated for 400 days and the behaviour of the system is monitored.

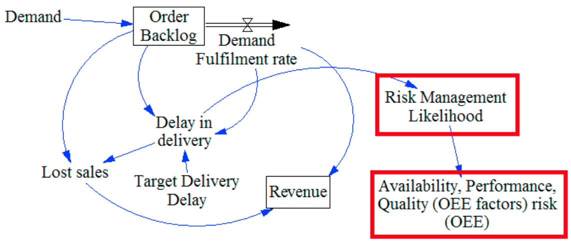


Fig. 9: Feedback loop from SD to BBN model – Case Study

4.3 Case Study – Risk Evaluation

The company was interested in understanding the impact of variations in the OEE risk and response time on the Fineblanking and grinding stations. Table 1 presents 16 what-if scenarios that were modelled. Table 2 shows the data used for the 'Normal' and 'High' scenarios for each station.

Table 1: Case Study Scenarios

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

Table 2: Variables used in simulation

		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

5. Results

Delivery performance has become important to Original Equipment Manufacturers (OEMs) and their suppliers as customers are inclined towards manufacturers/service providers having reduced lead times. Hence, "Delay in delivery" performance metric was chosen to compare between scenarios and analyze system's behaviour.

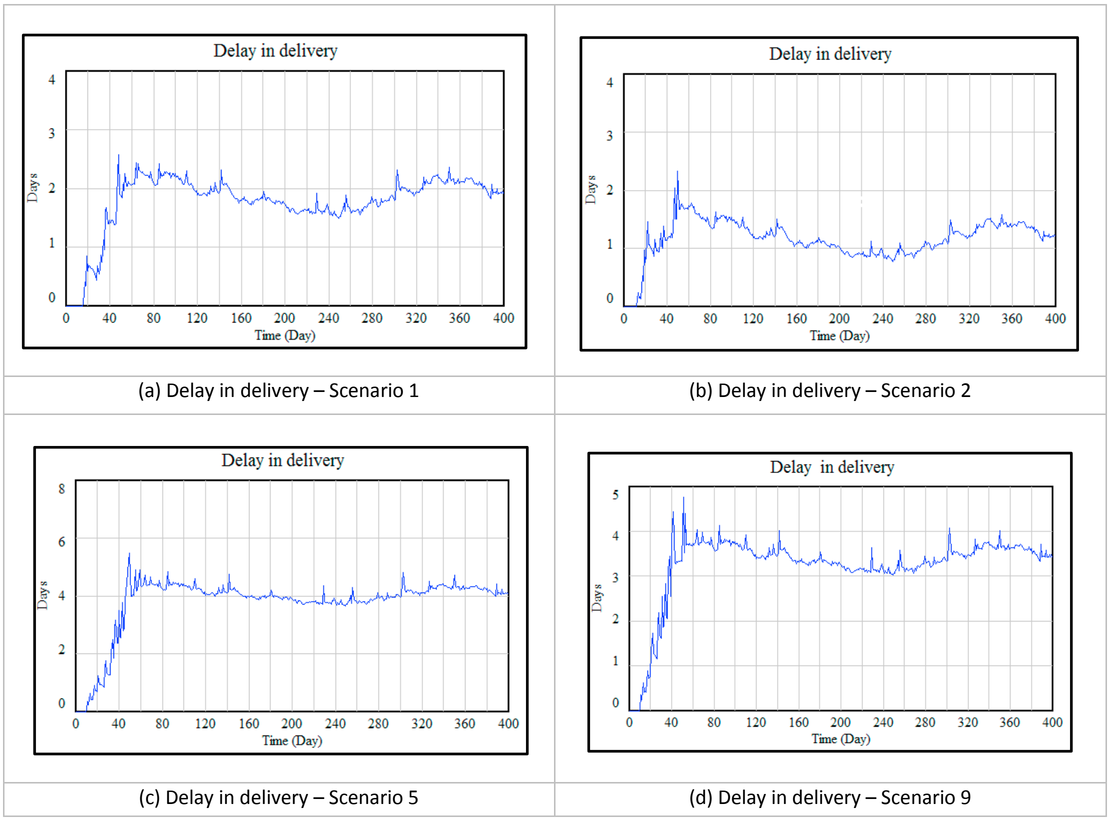
5.1 Scenarios analysis – delay in delivery KPI

The baseline model shows no delay in delivery, thus leading to maximum revenue. The cumulative revenue generated is $4.132 million over a period of 400 days. Scenarios analysis revealed some interesting aspects about the system's behavior which otherwise would have been neglected. Fig. 10 displays the performance of the line under a few scenarios (selected based on the trend observed) through "Delay in delivery" performance metric. Some of the interesting observations are:

a) Scenario 1, in Fig. 10(a), has a higher delay in delivery when compared to scenario 2, in Fig. 10(b), despite having a lower risk impacting the line. With a higher risk at the fineblanking station in scenario 2, the delay in delivery is quite high initially. This high delay results in a higher risk response likelihood and this in turn results in an increased risk mitigation. Due to the increased risk mitigation, "Delay in delivery", in scenario 2, in the latter part of simulation is much lower when compared to that of scenario 1

b) Contrary to observation (a), scenario 1 and scenario 5 show a different trend. Scenario 5 shows a higher delay in delivery despite having a higher risk response likelihood. The reason for this is that the grinding station is the bottleneck process and any manufacturing delay at the grinding station is tough to compensate for.

c) Scenario 5 shows a higher delay in delivery than in case of scenario 9 despite having a high risk at just the grinding station. In scenario 9, a higher risk at both fineblanking and grinding stations results in a higher “Delay in delivery” initially. This results in an increase in risk response likelihood and thus leads to risk mitigation. Hence, a lower delay in delivery is seen towards the latter part of simulation in scenario 9.



(a) Delay in delivery – Scenario 1

(b) Delay in delivery – Scenario 2

(c) Delay in delivery – Scenario 5

(d) Delay in delivery – Scenario 9

Fig. 10: Delay in delivery – scenarios analysis

Almost all delay in delivery was due to the low difference between demand and demand fulfilment rate. A delay in delivery was bound to occur during a risk event. Most of the production delays occurring during a risk event were carried until the end of simulation period. However, industrialists have several action plans to recover production losses. Overtime is the most common way of resolving this issue.

5.2 Effect of overtime on scenarios

Extra capacity (through overtime) was added to a few scenarios, which were selected based on initial results, and simulated for 400 days. Overtime of 7.5 hours/day, 3.75 hours/shift, when the delay in delivery exceeds 1.5 days. An overtime cost was associated with the revenue equation.

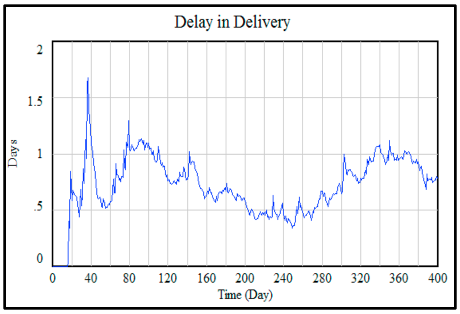
Extra capacity added was deterministic in nature in order to simplify the case. Fig. 11 displays the results of this experiment.

a) Scenario 1: As seen in Fig. 11(a), performance of production line improves and delay in delivery stays under one day for the majority of simulation period. Cumulative revenue shows an increase of $650,000 with added capacity.

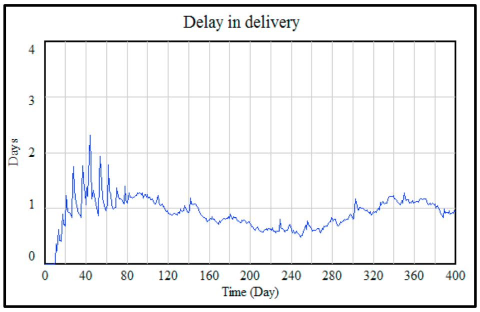
b) Scenario 5: As seen in Fig. 11(b), extra capacity is added during the initial phase of the simulation period when a high risk was affecting the line. Cumulative revenue increases form $3.73 million to $3.75 million when extra capacity (overtime) is utilized.

c) Scenario 11: As seen in Fig. 11 (c), scenario 11 also shows a significant improvement in performance with added capacity and aggressive risk response. Cumulative revenue increases from -$1.4 million to $3.719 million.

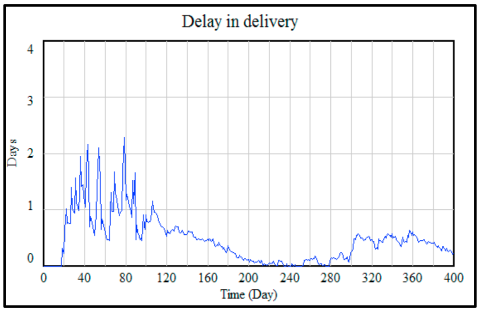
d) Scenario 16: As seen in Fig. 11(d), extra capacity is utilized several times initially. Risk response and extra capacity reduce the delay in delivery to a huge extent. There is no delay in delivery after 130th day. Cumulative revenue increases from $1.735 million to $3.936 million.



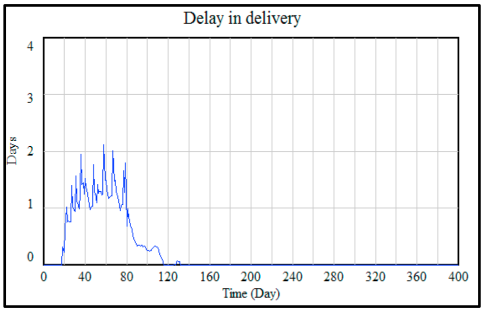
(a) Impact of added capacity on scenario 1



(b) Impact of added capacity on scenario 5



(c) Impact of added capacity on scenario 11



(c) Impact of added capacity on scenario 16

Fig. 11: Impact of added capacity on scenarios

6. Conclusions

The proposed PLRA methodology provides a versatile technique to assess the impact of risks affecting production line performance. The BBN model captures relationships between risk events and calculates their likelihoods. The dynamic nature of this BBN model is captured by combining it with SD production line model. The impact of risk events on the production line is examined through various KPIs.

Comparing the production line model (affected by risks) to the baseline model shows a “Delay in delivery” of 1.5-2 days resulting in a loss in revenue of almost $900,000. Further, analyzing several scenarios enables understanding numerous key aspects of the system’s behavior.

These results not only confirm the importance of risk assessment at the production line level but also act as a great reference for production planning and risk management units. The likelihood of risk exposure is well captured through BBN and the impact of risks on production line KPIs like delay in delivery, demand fulfilment rate and revenue through SD. This combined approach of SD-BBN bridges the research gaps identified with the current techniques of risk assessment.

Future work would include an extended risk taxonomy at the production line level and adding back propagation capability. Back propagation is one of the key features of BBN, which help calculate the likelihood of parent nodes based on the likelihood of child node, thus identifying the root cause.

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