Supplier Risk Management using Bayesian Network Analysis

ISEN 660

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Abstract

The focus of this project is to understand, explore and try to mitigate the factors causing delays in the production of the engine component. Based on experience and historical data, observation was made that the suppliers' inability to meet the requirements is the most common cause. To analyze the problem better Bow-Tie analysis is done to help narrow down the project's scope to supplier factors and their mitigation methods. Using the actual production process of an engine sub-component assembly, a fault tree is created with top events as a delay in production and the basic events as Suppliers. Cut Sets are identified from the fault tree, and the probability of disruption of suppliers is calculated using a Bayesian network of three factors: Network risk, operational risk, and external risks; using this disruption probability, we ranked the Cut sets and Suppliers based on the criticality. Assuming 30% safety stock as a company policy, we calculated the Order Placed to each supplier based on the facility's Monthly demand requirements and then calculated the number of shortages received from each supplier. The calculation of the total components that can be produced is done from the demand and the number of parts received. Based on critical suppliers identified earlier, the recommendation is to consider onboarding new suppliers to either serve as backup or to have multiple suppliers supply the required parts. For this purpose, the implementation of a new supplier evaluation tool using the bayesian network incorporating factors of primary, green, and resiliency risks is demonstrated.

Keywords: Bayesian Network Analysis, AgenaRisk, Bowtie, Cutsets, Fault Tree, Risk Analysis, Resilience

1. Introduction

1.1 Motivation

The automobile industry is one of the gravely impacted sectors of manufacturing due to global supply chain issues that prevail post-pandemic due to supply chain pipeline disruptions. This has caused production delays, affecting the automotive manufacturers' promise to meet customer demands lately. As this industry is excessively dependent on Tier 1 suppliers, manufacturers must spend a considerable chunk of their budget buying goods and commodities. Recent times have led them to spend more on procuring said items. It has also increased their storage costs as they have to stockpile unfinished cars waiting for their components.Along with that, they have to incur losses related to delays in supply time due to issues at the supplier end as they have to face the same problems. Therefore, supplier evaluation should be done more efficiently to mitigate production delays further and increase the organization's overall profit margins. Overall, industries employ their primary supplier evaluation criteria like Quality, Cost, and Deliverables parameters (QCD), wherein they look for high quality, lower costs and higher deliverables, and lower Minimum Order Quantity (MOQ) with that they use their risk strategies. Furthermore, since automotive industries rely highly on suppliers, they need reliability. However, fewer suppliers selected specific supplier risk evaluation criteria to predict and handle risk taking into account the uncertainty of the decision-making process with reliable results based on their supplier profiles to avoid disruptions in supply chain performance and production timelines such as Bayesian Network analysis.

1.2 Literature Review

This paper illustrates how organizations can use the Bayesian network to assess the impact on buyers by benchmarking their supplier risks. It considers variables like network and internal and external risk probability for risk assessment. This method can be utilized to evaluate supplier performance risks, replace or develop multiple organizations' existing strategies, and asses their current suppliers. It also provides a foundation to explore further how a Bayesian network model can prove to be a reliable technique to increase the efficiency of the supply chain network of organizations and help the procurement team in better analysis during the selection of suppliers.

This paper proves that along with the traditional supplier selection criteria, i.e., primary, which includes lead time, cost, quality, and green criteria, which makes the inclusion of how green or how close the Supplier adheres to the environmental preservation practices there should be a third criterion on resilience. According to this paper, resilience relates to how fast a supplier can recover to the desired level of efficacy within the shortest available time period after disruption in the supply chain network. Natural calamities which prove inevitable, like earthquakes or flooding or events in recent times, such as pandemics, prove to be a threat to supply chain networks. Therefore, these suppliers that can withstand the adversary should be considered equally. This paper also utilizes the method of the Bayesian Network to analyze supplier selection criteria for resilient suppliers based on the above-motioned criteria.

1.3 Background and Info

This project assumes an automobile manufacturing industry for the model, with the data set assumed from the domain knowledge and experience of the project members throughout the internship and previous jobs. Also, some data is being collected from internet resources. It focuses on the production of the critical component of the Engine, which has three subcomponents that are supplied by four assembly lines and supported by various combinations of suppliers [see fig below]. The detailed production process is explained in the methodology section.

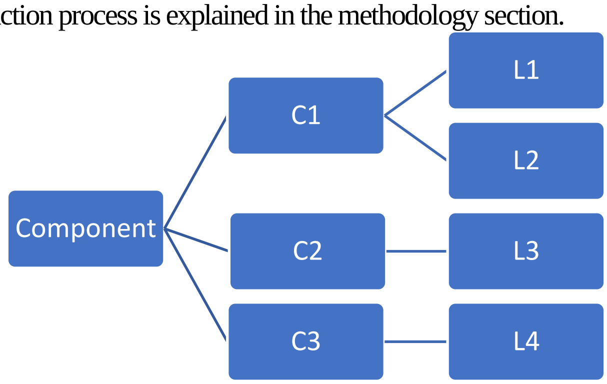


Figure 1: Production process flow diagram

1.4 Limitations

1. An automotive manufacturing plant is a highly complex organization with different entities working in tandem with each other; in this model, we are only considering the production of 1 component.
2. There can be many factors contributing to the delay in production. Still, in our project, we focus only on the Supplier and how the risks involved in selecting this Supplier are essential and ignore the interconnecting complexities.
3. Limitation of Data - the effectiveness of the model depends on the Supplier's willingness to contribute data for evaluating their risk profiles; in our problem, we have assumed the relationship among different factors and its impact on the top event, but ideally, data provided from suppliers should be used directly.
4. Here, multiple factors can affect the Supplier's ability to meet the Demand, but in this project, only significant factors have been used.
5. The Bayesian network developed is based on various assumptions, research papers, and the team's experience, so there can be cases where wrong assumptions can be made. In future studies, an approach can be made to formulate the network based on data.

1.5 Concepts

1.5.1 Bayes Theorem

In probability theory, Bayes theorem tells us to update our belief in a hypothesis based on evidence that we have, which means that given an event B has already occurred, it determines the conditional probability of event A. Mathematically, it is written as P(A|B). It can be calculated if we know the probabilities of occurrence of Event A, Event B, and the conditional probability of B given A.

$$\Pr(A|B) = \frac{\Pr(\mathrm{B/A}) * \Pr(\mathrm{A})}{\Pr\,(B)}$$

1.5.2 Bow-Tie Analysis

Bow-Tie Analysis involves identifying potential hazards, developing risk scenarios, and assessing risk. It helps us to interpret complex risk scenarios by mapping risk events, root causes, risk mitigations, and consequences in a graphical diagram. In addition, it can prevent the top event from happening. Based on the risk timeline, bow tie analysis has four essential components: causes, events, impacts, and controls from left to right. This method is very beneficial in estimating risk and identifying consequence of an event in the model going from left to right.

1.5.3 Fault Tree Analysis

Fault tree analysis is a diagrammatic representation of the failure chain of events that occur, and it gives us interrelationships between a system event and its causes. It is a top-down approach which means if we come across an issue in the system, we can show all the factors causing these problems using Fault tree Analysis. It has only three components top event, basic event, and logic gates. The events and logic gates connect to identify the cause of the top undesired event. It is used mainly to find out the cause of the system failure and mitigate the risk before it occurs.

1.5.4 Cut sets

Set of basic fault tree events that lead to top event occurrence. This is usually a list of failures in a fault tree; a single combination or multiple combinations can lead to the top event. All the different combinations are called cut sets. Cut sets are used for validation, model understanding, and common mode analysis.

$$I_e = \frac{\sum_{e}^{N_e} I_{Ke}}{P_T}$$

$$I_k = \frac{P_K}{P_T}$$

1.5.5 Bayesian Network

They are probabilistic graphical models that use different kinds of logic, knowledge, and rules. It uses concepts of Bayes theorem and conditional probability to know the dependency among the components in the system. It has a set of variables and conditional probabilities with a directed acyclic graph. If an event occurs and we know the possible reasons why the event has occurred, then the Bayesian network model helps us see the likelihood that any of the causes is the main factor.

1.5.7 Agenarisk

It is a software that uses Bayesian Statistics and probabilistic methods to solve complex problems and help decision-making. Agenarisk helps decision-making analyze risks in a way that is an auditable, repeatable way or risk planning. It is useful when there is little to no data.

2.0 Methodology

Here in the paper, we have performed bow-tie analysis considering the hazard as manufacturing of automobile components and the top event as delay in production, the potential causes identified in table 1. We then designed a fault tree based on our collective domain knowledge for an assembly line in an automobile manufacturing plant. After making the fault tree, we created a Bayesian network in Agenarisk by incorporating a few essential parameters. The Bayesian model considers five different suppliers to an automotive company. The model considers various types of risk, like network, operational, and external. Under each category, we have included different types of risk like misalignment of interest, supplier leadership change, transportation issues, etc. We calculate all suppliers' supplier disruption probabilities and predict how likely they are to fail. To do this, we got the individual probabilities of each parameter from a reference paper [1] and calculated the joint probabilities by assigning weights. We can predict how likely a supplier will fail based on the probabilities we get from Agena Risk. On getting the probabilities from Agenarisk and identifying the cut sets from the Fault tree, we gave ranks on which supplier is more likely not to meet the demand.

The data used in the model is assumed from previous knowledge and inference. In table 1, we have the data on delays in production for various reasons like supplier and manpower issues. From the data, we can see that majority of issues are from production delays.

Reason	Quantity
Supplier Issue	12950
Weld Issue	650
Paint Issue	750
Production Issue	635
Manpower Issue	2450

Table 1: Data of delay in production

We have the individual priori of 5 different suppliers we considered in the Bayesian network from a research paper [1], and we have assigned weights to all of them. Here A, B, C, D, and E represent the suppliers we are considering in our production system. ‘P’ is the prior probability, and ‘W’ is the weight given to each parameter shown in Table 2.

2.1 Distribution

The distribution model for demand data is continuous, and the data source is from GitHub [3]. A histogram was plotted for data visualization to get a better perspective on the acquired data. The data was run through 4 different distributions to get the best fit from the plot, namely normal, gamma, triangular and exponential, based on the outcome of the histogram. A KS goodness of fit test was used to validate the best fit out of the four, as it is best for small and continuous data. The results indicated the data followed a normal distribution curve with a mean of 1343.688 and a variance of 228354.958. The lead time data was obtained from the shipment orders dataset from another ISEN course. [11]. which provided shipping dates and the goods received note (GRN) dates, and the difference between them was calculated, which is our lead time. This data is discrete; hence it was fit through the Poisson distribution, and since t-test was used since it’s a better test than the KS test for discrete distributions. The graphs Figs 2 & 5 show the visual representation of the data used in the model along with the Q-Q plot in Fig 3.

2.1.1 Demand

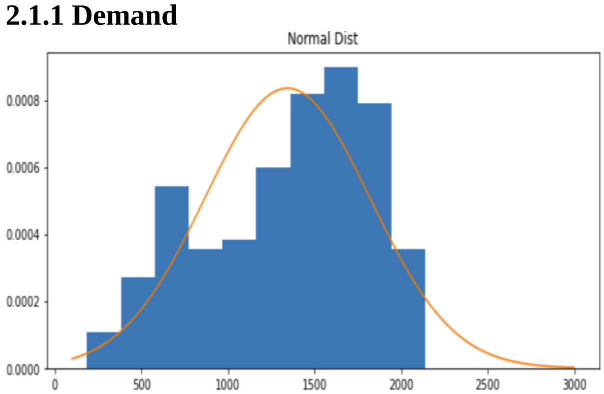


Figure 2: Demand Value vs Frequency

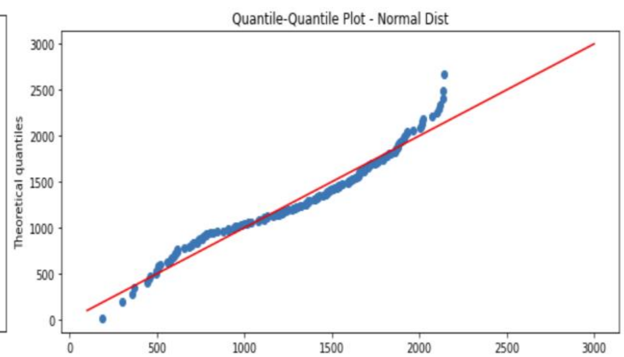


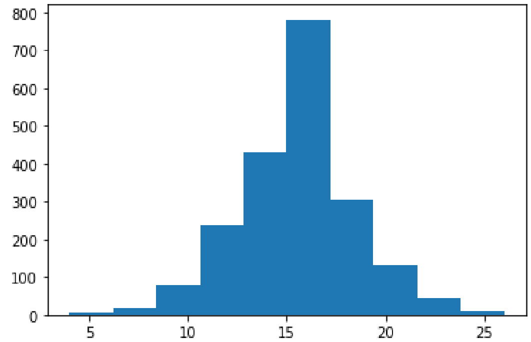
Figure 3: Q-Q Plot

```
# Normal Distribution
u,s=ss.norm.fit(demand.Demand)
print(f"The maximum Likelyhood estimators for Normal Distribution are: mean is \
{round(u,3)} and std is {round(s,3)}")

The maximum Likelyhood estimators for Normal Distribution are: mean is 1343.688 and std is 477.865
```

Figure 4 Normal Distribution code and result

2.1.2 Leadtime




```python
from scipy.stats import poisson
mean, var, skew, kurt = poisson.stats(mu,moments='mvsk')
x = np.arange(poisson.ppf(0.01, mu),poisson.ppf(0.99, mu))
poisson_act= poisson.rvs(mu, size=len(leadtime_df["leadtime"]))
from scipy.stats import ttest_ind
t_stat, p_value = ttest_ind(poisson_act,leadtime_df["leadtime"])
```

```python
p_value
```

```
0.7396074821534913
```

Figure 5: Lead Time vs Frequency

2.2 Bowtie Analysis

The bowtie analysis considers the hazard as manufacturing of automobile components, having a top event of delay in production. Therefore, the analysis's left-hand side represents the top event's root cause issues, viz. supplier, manpower, weld quality, paint quality, and production issues. Whereas the right-hand side portrays the consequences of the top event, namely revenue loss, customer dissatisfaction, and loss of reputation, all being critical to the assumed automobile manufacturer.

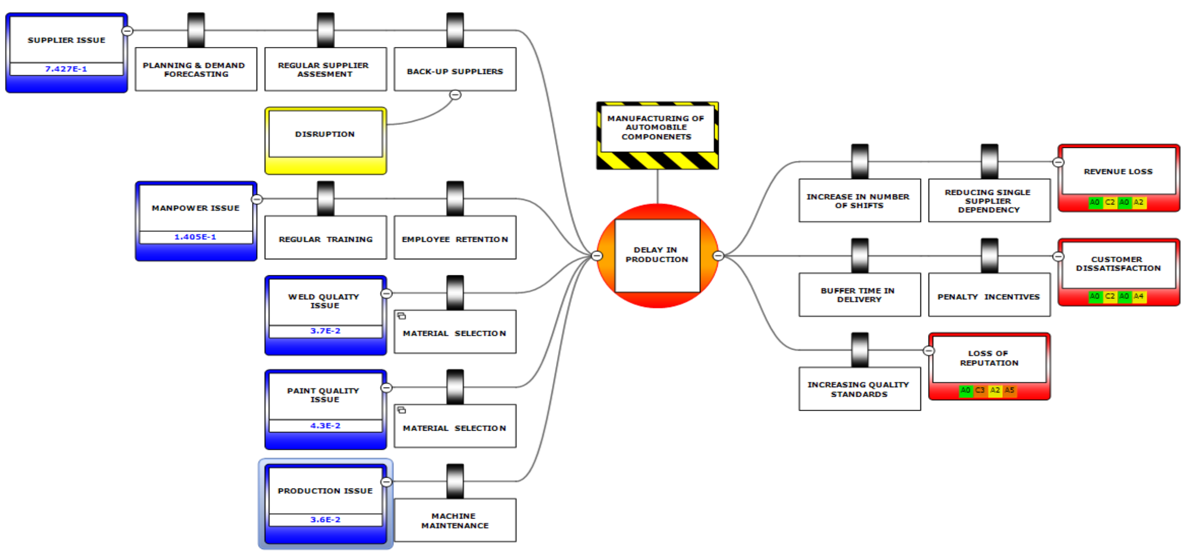


Figure 6: Bowtie Analysis

The analysis sets several preventive barriers to each of the root causes, such as planning and demand forecasting, regular supplier assessment, and having backup suppliers for the high-risk suppliers identified on the supplier panel. One of the issues with backup suppliers is disruptions, as they could face the same issue as the others if the disruptions in the supply chain pipeline are global, like the recent pandemic of Covid-19. We can prevent manpower issues through regular training and better employee retention policies. At the same time, the issue of weld quality can be resolved by selecting proper or standardized materials for the process, which is also the case for paint quality issues. An appropriate regime of well-planned

machine maintenance can solve issues in production like line stoppages or slow production. The recovery barriers are increasing the number of shifts of employees and reducing the dependency on a single supplier. Keeping a buffer in the delivery time and introducing the policy of penalty incentives like bonus offers to prevent customer dissatisfaction and a subsequent increase in the quality of the product can increase the manufacturer's reputation.
After considering the above parameters probability of occurrence of the said root causes has been calculated from the data in Table 1, with supplier issue having a probability of occurrence of 0.7427, manpower having 0.1405, weld quality having 0.037, paint quality issue with 0.043 and production issues the probability of 0.036. The calculations show that supplier issues are the major cause of delay in production based on the results; hence the model focuses on the risks associated with the suppliers by using fault tree analysis and Bayesian network analysis.

2.3 Fault Tree Analysis:

Based on bow tie analysis results, the fault tree analysis focuses on the delay in production as the undesired event of the tree, with the suppliers being the basic events and following a reactive approach. The fault tree layout is designed based on our collective experiences and domain knowledge for analysis purposes.

As sub-component 1 is the most critical, it is produced in 2 lines where raw materials for Line 1 are supplied by supplier A which has to be welded moving to the production line. Raw material for Line 2 is supplied by Supplier B & C for the production line 2, which needs to be welded together and painted. For production line 3, one of the parts comes from supplier C and the other is from Supplier D or E, which needs to be welded and painted. Finally, for production Line-4 parts are either outsourced from Supplier C or D or they can be insourced (Limited capacity available) and welded before use.

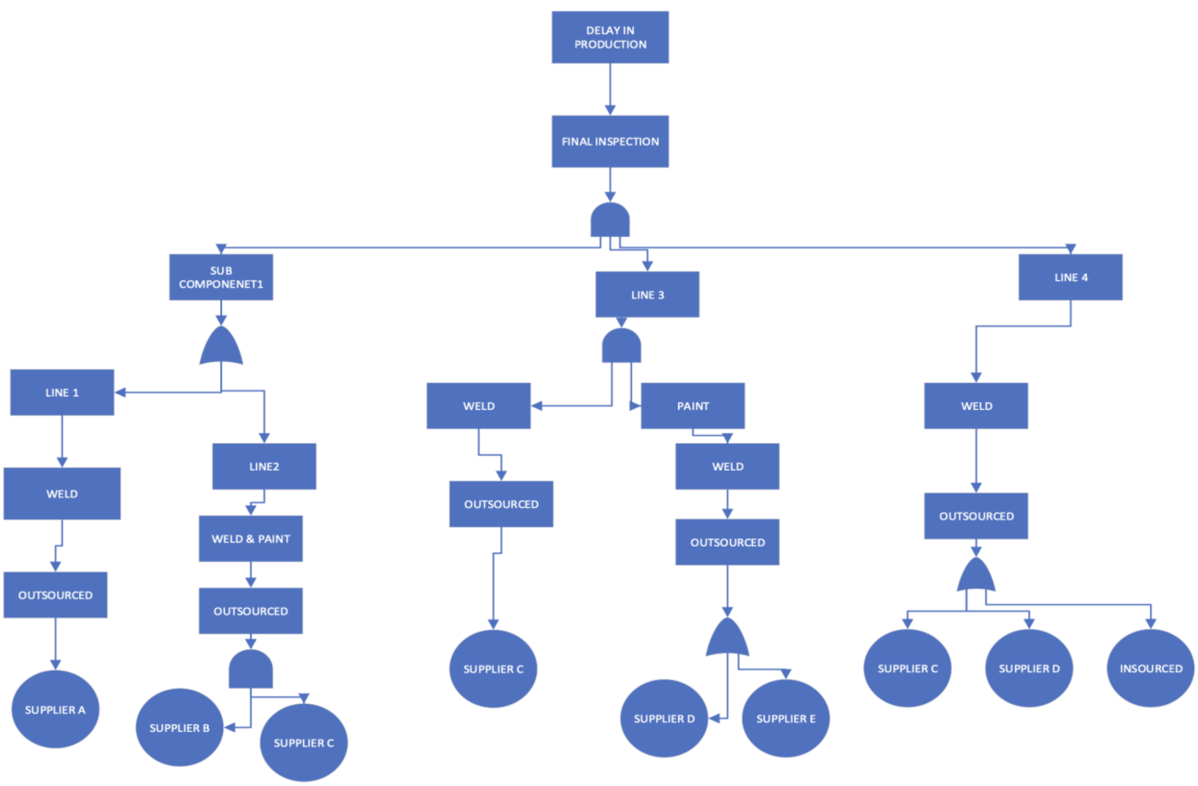


Figure 7: Fault Tree Analysis

2.4 Cut Sets:

The flowchart below portrays the contribution of each supplier towards the assembly, it is designed in accordance with the Fault Tree. The contribution of goods required from each supplier to ensure that the monthly demand of engine sub-component is depicted in the flowchart in Figure 8 (calculated based on BOM). According to the bill of material of engine sub-components, 4-unit goods of SC1, 1-unit goods of SC2 and 2 unit goods of SC3 are required to make 1 unit of the engine sub-component. 50% goods required for SC1 are purchased from Supplier A and 50% goods required for SC1 are purchased from both Supplier B and Supplier C cumulatively (To make SC1 on line-2 both suppliers B and C provide different raw materials this is why Line-2 takes more time to produce SC1 in comparison to Line 1) 100% goods required for SC2 are purchased from Supplier C, and 60% goods required for SC2 are purchased from Supplier D and 40% goods required for SC2 are purchased from Supplier E. 25% goods required for SC3 are purchased from Supplier C, 50% goods required for SC3 are purchased from Supplier D and 25% goods required for SC3 are purchased from Supplier D. Demand data for assembly of engine sub component is obtained to be 1343.33 per month which is rounded off to 1350

Therefore, the units required by the company from the suppliers are as follows:

Supplier A = 1350 X 2 = 2700 units of goods

Supplier B = 1350 X 2 = 2700 units of goods

Supplier C = 1350 X (2 + 1 + 0.5) = 4725 units of goods

Supplier D = 1350 X (0.6+1) = 2160 units of goods

Supplier E = 1350 X 0.4 = 540 units of goods

The general order policy the company follows is Order Placed = Demand + Safety Stock. The Safety Stock initially assumed by the company is taken to be 30 % for goods purchased from the 5 suppliers.

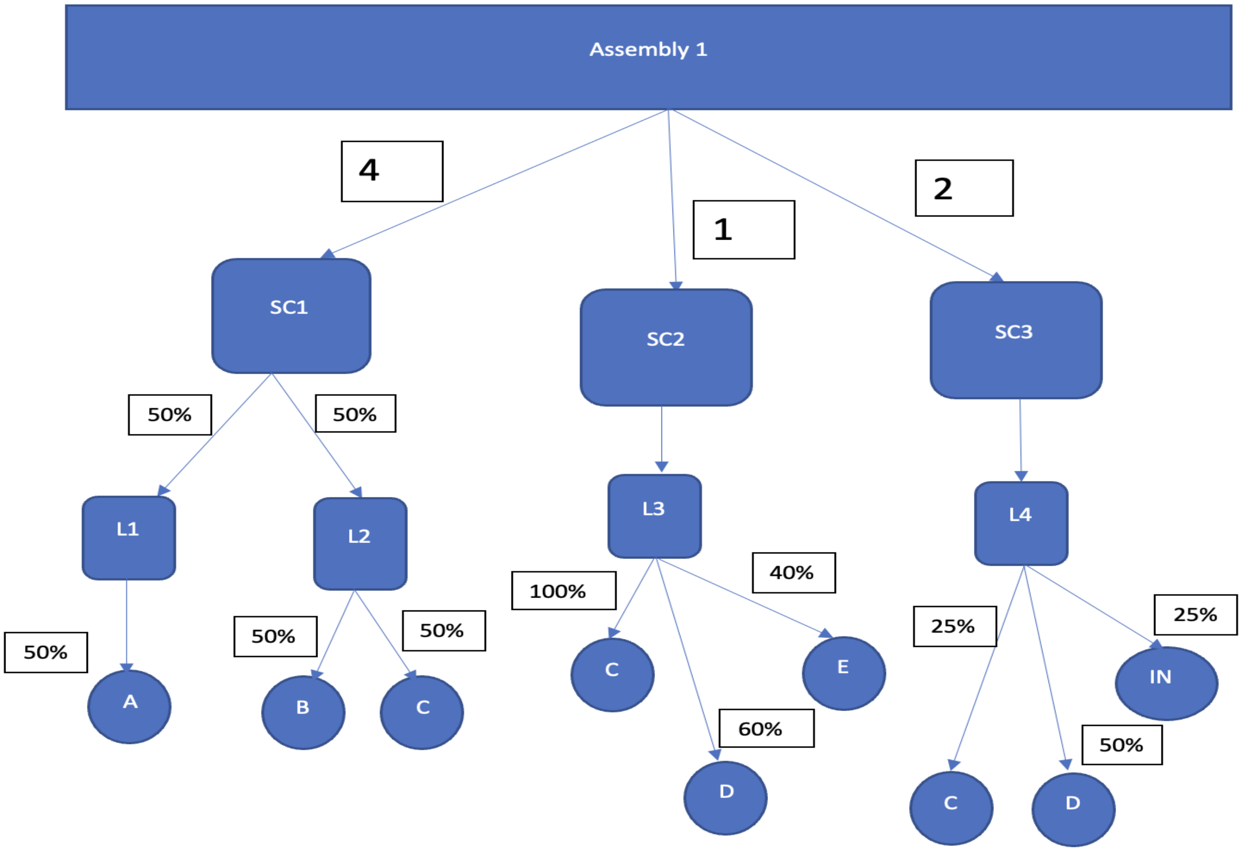


Figure 8: Cut Sets of Fault Tree Analysis

2.5 Bayesian Network Analysis

2.5.1 Evaluating Supplier Disruption Probability

To calculate the probability of disruption of suppliers (we have considered data during the Covid-19 pandemic period, hence a huge variation in the probability of factors is observed – that's also why we are not considering the impact of disruption due to covid separately) we considered 3 factors which are as follows:

1. Network Risk: This risk comprises of suppliers both internal (communication, information flow, financial) as well external (controllable) risk. For our model we have considered 4 network risks defined below:
   a) Misalignment of Interest – Due to some unforeseen scenario the supplier might not be aligned to meet the standards or expectations of our demands.
   b) Supplier Financial Risk – The risk of the supplier facing financial issues (maybe facing bankruptcy or not being able to extract payment from its customers etc)
   c) Supplier Leadership Change – Maybe because of new leadership coming in there can be disruption in the production flow or during covid because of the large firing of employees there has been increasing distrust among workers thus affecting production.
   d) Tier-2 Stoppage - Due to the loss of production from Tier-2 suppliers, there is a lack of raw materials, and production is impacted.
2. Operation Risk: The loss of production focusing on the supplier's inability to supply the products in a satisfactory manner, 2 factors are considered:
   a) Quality Problems - Parts of Poor Quality
   b) Delivery Problems - Delay in delivery or Damaged Parts received during transit.
3. External Risk: These are those risk factors that we cannot control and are affected by factors like Environment, market conditions, etc. 2 factors considered here are:
   a)Supplier Locked – Inability to switch to a different supplier. Maybe because of lack of any other source, government contract, etc.
   b)Disaster – Any Natural or accidental disaster like an earthquake, Facility burned due to Fire.

The tables below show the prior probability of the various factors for the 5 suppliers:

Network Risk				
Supplier	**Misalignment of Interest**	**Supplier Financial Stress**	**Supplier Leadership Change**	**Tier-2 Stoppage**
A	0.2	0.5	0.5	0.31
B	0.17	0.23	0.2	0.13
C	0.2	0.2	0.5	0.31
D	0.16	0.33	0.23	0.16
E	0.19	0.38	0.23	0.17

Operation Risk			External Risk		
Supplier	**Quality Problems**	**Delivery Problems**	**Supplier**	**Supplier Locked**	**Disasters**
A	0.46	0.2	**A**	0.18	0.11
B	0.23	0.46	**B**	0.06	0.08
C	0.48	0.95	**C**	0.18	0.12
D	0.21	0.52	**D**	0.09	0.1
E	0.22	0.53	**E**	0.11	0.13

Network Risk		Operation Risk		External Risk	
Factors	**Weight**	**Factors**	**Weight**	**Factors**	**Weight**
Misalignment of Interest	1	**Quality Problems**	2	**Supplier Locked**	2
Supplier Financial Stress	2	**Delivery Problems**	2	**Disasters**	3
Supplier Leadership Change	1				
Tier-2 Stoppage	2				

Table 2 Prior Probability and Weighted Mean

Without proper data, it's very difficult to assume the joint probabilities of the various factors that's why we leveraged the Ranked nodes feature of Agena Risk. Based on our collective experience, we made a judgment call and ranked each factor from 1 to 3 where weight of 1 least impact and weight of 3 means most impact (almost entire production process is impacted. The weight assigned to various factor based on collective judgement of group is mentioned below. Also, the weights for each Network risk, External Risk and Operation risk kept same assuming that all the components will have similar impact on the supplier disruption.

$$Weighted\ Mean\ = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i}, \qquad where\ w_i \geq 0$$

2.5.2 Supplier Evaluation Method

To select a supplier, we have considered three criteria and categorized them as Primary Criteria, Resilience Criteria, Green Criteria.

a) Primary Criteria

Variable	Node Probability Table	Meaning
Probability that a product is faulty (Sub-variable)	Beta (α =0.8, β =30, LB=1, UB=0)	Probability that product shipped from the supplier to the production company follows Beta distribution
Quality of Products(M14) (Variable)	If (Probability<0.06, “True”, “False”)	Probability that a product is faulty is less than 0.06 then the product should be acceptable)
Total Costs(M13) (Variable)	if((M22+M19)>80,000,"True","False")	If the sum of the total costs of the supplier is less than budget allocated, then select the supplier, else don’t select
Order Cost(M22) (Sub-variable)	Constant = 1000	Order Cost we selected is 1000
Purchased items(M23) (Sub-variable)	min (M1, M0)	The items we purchase from the supplier should always take the minimum cost of Demand and the capacity of the supplier
Purchase Cost(M19) (Sub-variable)	M3*M23	It’s the Product of Purchase Cost per product and purchased items
Purchase cost per Product(M3) (Sub-variable)	Constant =24	We Selected purchase cost of product to be 24

Demand(M0) (Sub-variable)	NORM (μ =1343.88, σ = 228354.958)	From the Demand Data fitted to Normal distribution
Capacity of the Supplier(M1) (Sub-Variable)	Constant=1000	Capacity of the supplier is 1000
Technical Support (Sub-Variable)	False=0.15, True=.85	Attribute of the Service level of the Supplier
After Sales Service (Sub-Variable)	False=0.1, True=0.9	Attribute of the Service Level of the Supplier
Delivery Robustness(M10) (Variable)	if(M9<16.0&&M8>0.9,"True","False")	Ability of the Supplier to meet the delivery Schedule
Lead Time(M9) (Sub-variable)	POISSON (μ =15.44)	Total time taken to deliver a product
Response Rate(M8) (Sub-variable)	TNORM (μ =0.94, σ = 0.01, LB =0.87, UB=1)	Response rate if we face any issues from the Suppliers

Table 3 Primary Criteria of Second Bayesian Analysis

The Noisy OR function is used to calculate the conditional probability of primary criteria which tells how likely a supplier is going to meet the primary criteria. For example, noisyor (Total Costs,0.2, Quality of Products,0.4, Service,0.15, Delivery Robustness,0.15,0.01) rpresents that the probability supplier will satisfy primary criteria is 0.2 if only the Total Cost parameter is satisfied, and similarly 0.4 for Quality, 0.15 for Service and 0.15 for delivery Robustness. The last parameter of 0.01 signifies the leakage factor which accounts for uncertainty i.e. probability of the supplier satisfying the primary criteria even if all other factors are not satisfied.

b) Green Criteria

Variable	Node Probability Table	Meaning
Distance Between the Supplier and the manufacturer	Constant=448km	Distance between the Supplier location and customer location
CO_2 emission	Follows a triangular distribution with (left=25, middle=120, right=150)	The CO_2 emitted because of transportation of raw materials from the supplier to the manufacturer
Total emitted CO_2	Distance * Total emitted CO_2	Distance * Total emitted CO_2

Table 4: Green Criteria of Second Bayesian Analysis

If Total emitted CO_2 is less than 53000 then the green criteria is met. We have only taken CO_2 emissions as it contributes nearly 94% of the greenhouse gas emissions.

c) Resilience Criteria

Variable	Node Probability Table	Meaning
Restorative Capacity(M3)	False=0.2, True =0.8	The ability of supplier to recover permanently from a disruption.
Adaptive Capacity(M2)	False=0.5, True =0.95	The ability to adapt to the disruptions and react to it.
Absorptive Capacity(M1)	Noisyor (M6,0.5, M5,0.15, M4,0.2,0.05)	The ability to absorb shocks from the disruptions and react to it.
Backup Supplier(M4)	False=0.4, True=0.6	Backup supplier that we need to keep just in case the first supplier fails to deliver it on time to us.
Surplus Inventory(M5)	False=0.23, True=.77	Backup inventory the supplier keeps just in case.
Disaster(M6)	False=0.2, True=0.8	Assume that natural disasters happen in the supplier.

Table 5 Resilience Criteria of Second Bayesian Analysis

Most of the data in the project is from a paper which focuses on supplier evaluation [2]. Based on our experience in the Supply Chain domain we made some changes to the data and modelled the Bayesian network in Agenarisk.

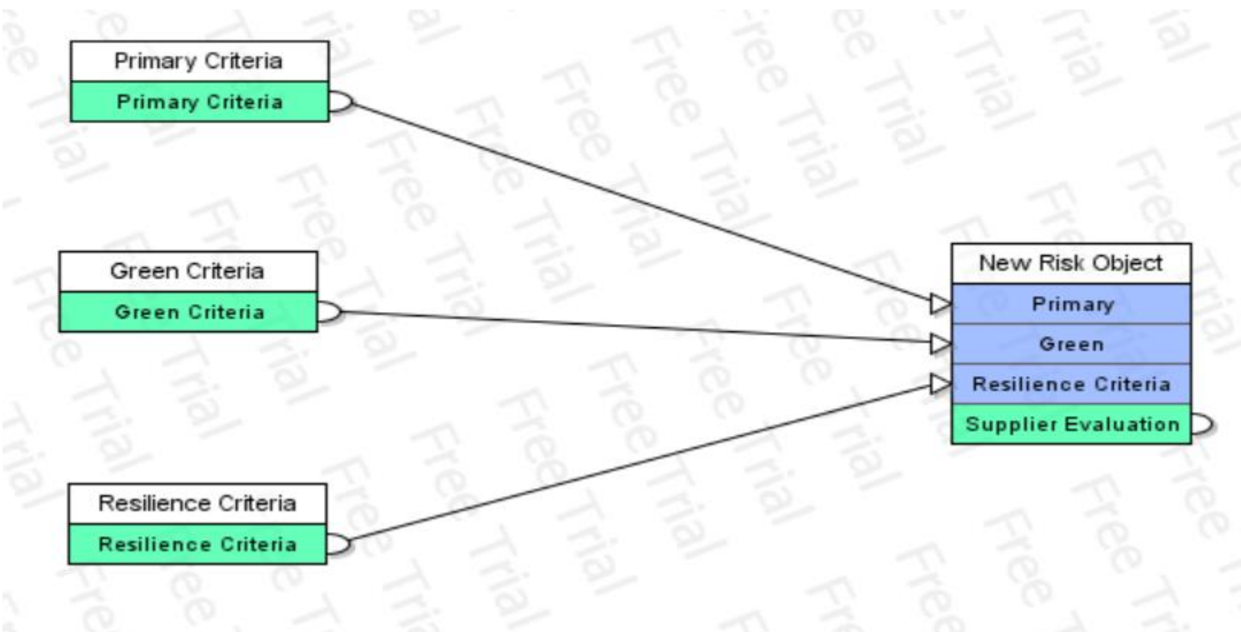


Figure 9 Bayesian Network of Second Analysis

3.0 Results – Bayesian Model-I

From the fault tree the Top Event is equal to Delay in Production

Delay in Production = Sub $Component_1$ X $Line_3$ X $Line_4$

Delay in Production = (SA + SB X SC) X SC X (SD + SE) x (SC + SC + INSOURCED)

Further Applying Boolean Logic

Delay in Production = SAxSCxSD + SAxSCxSE + SBxSCxSD + SBxSExSC

Hence the Cut Sets are C1=(SAxSCxSD), C2=(SAxSCxSE), C3= (SBxSExSC), C4= (SBxSCxSD)

We obtain the probability of supplier disruption from the Bayesian Model:

Supplier	Supplier Disruption Probability
A	0.45924
B	0.36945
C	0.45821
D	0.37964
E	0.38774

Table 6 Supplier Disruption Probability

The Probability of Top Event (PT)= 0.150769545 (Summation of the probabilities of failure of the cut sets)

Cut Set Importance Ranking:

Cut Set	Probability of Cut Set	Importance of Cut Set	Rank
C1	0.079887023	0.5298618	2
C2	0.081591492	0.5411669	1
C3	0.065638831	0.4353587	3
C4	0.064267617	0.4262639	4

Table 7: Cut Set Importance Ranking

C2 set is the most critical one and more likely to fail than the others, followed by C1, C3 and C4 Initiator Importance & Ranking:

Supplier	Cumulative Probability	Rank
SA	0.161478515	2
SB	0.129906449	5
SC	0.291384964	1
SD	0.14415464	3
SE	0.147230324	4

Table 8: Cumulative Probability

Hence the highest risk is associated with Supplier C, the risk associated with other suppliers in decreasing order is as follows Supplier A, Supplier D, Supplier E and Supplier B.

Supplier	Demand	Safety Stock	Goods Ordered	Disruption Probability of Supplier	Goods Supplied by Supplier after disruption	Shortage of Goods
A	2700	30%	3510	0.45924	1898	810
B	2700	30%	3510	0.36945	2213	810
C	4725	30%	6143	0.45821	3332	1418
D	2160	30%	2808	0.37964	1742	648
E	540	30%	702	0.38774	430	162

Table 9: Supplier Data

Supplier C provides 6150 units instead of 6143 because of their policy to produce components in a batch size of 50. In Table 9, the demand column mentions the units of goods required from suppliers to meet the monthly target. Safety Stock is taken to be 30% per the company's policy. The orders placed to suppliers after considering the safety stock are shown in the Units of goods ordered column. The Disruption probability is taken from the Bayesian Network Analysis performed for each of the suppliers during the peak of the Covid-19 pandemic. Considering supplier disruption probability during Covid, the actual units the supplier can supply are given in the column, Unit of the goods provided by the supplier after a disruption. The shortage of goods at the production facility due to the suppliers is calculated based on the difference between the unit of goods supplied by the supplier after disruption and the demand of units of goods required from each supplier. The shortage of goods by Supplier C is greater than any of the suppliers, which can also be seen from the Initiator Importance Table.

The Bayesian Model, as created in Agena Risk, is depicted in Fig10. In this, we are calculating the disruption of disruption in the operation of each supplier. (That is 25% probability of disruption means the supplier would fail shortly by 25% of the demand placed) The Bayesian model developed is used to evaluate the disruption probability of 5 suppliers currently being used in our process. This result is used for the analysis of the Fault tree (as described below).

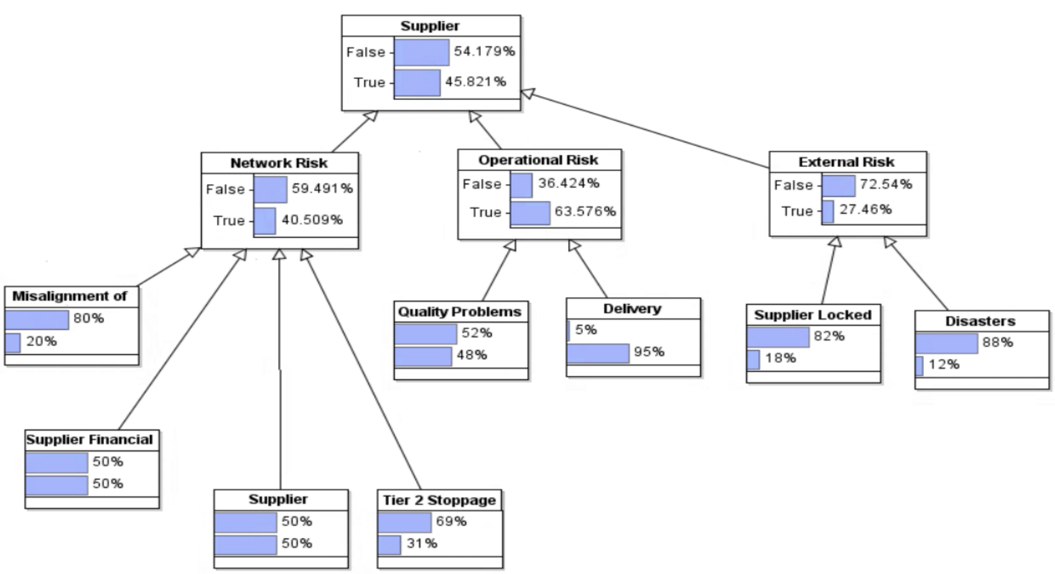


Figure 10: Bayesian Model 1

3.1 Sensitivity Analysis

To validate the results generated from the Bayesian network we validated by seeing the Tornado Graphs Fig 11 & 12 and looking at the conditional table between the top event and each factor. The analysis below is depicted for one critical supplier which is supplier C in depth. Tornado plots are often used to test the validity of the model and to understand how the target variable is being affected by other factors. The bar length represents the measure of the impact of each feature on the target node. As we can see from the tornado analysis Network Risk, Operational Risk and external risk all have a similar impact on the target Node and logically it's correct as well because an equal weight of 1 is assigned to each of them. Also, we can observe that Leadership changes are the property that has minimum impact on the supplier's ability to meet the demand.

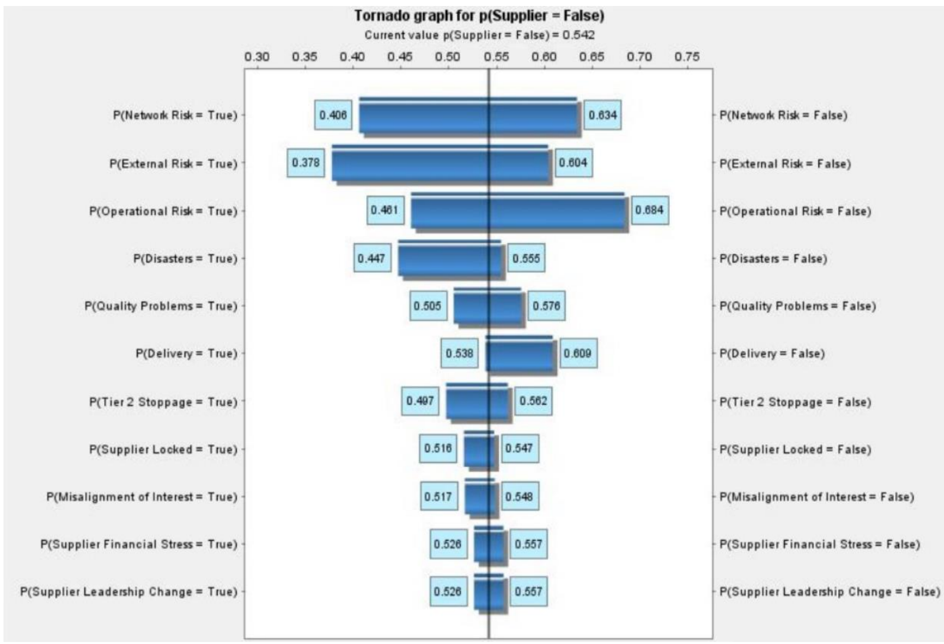


Figure 11: Tornado Graph 1

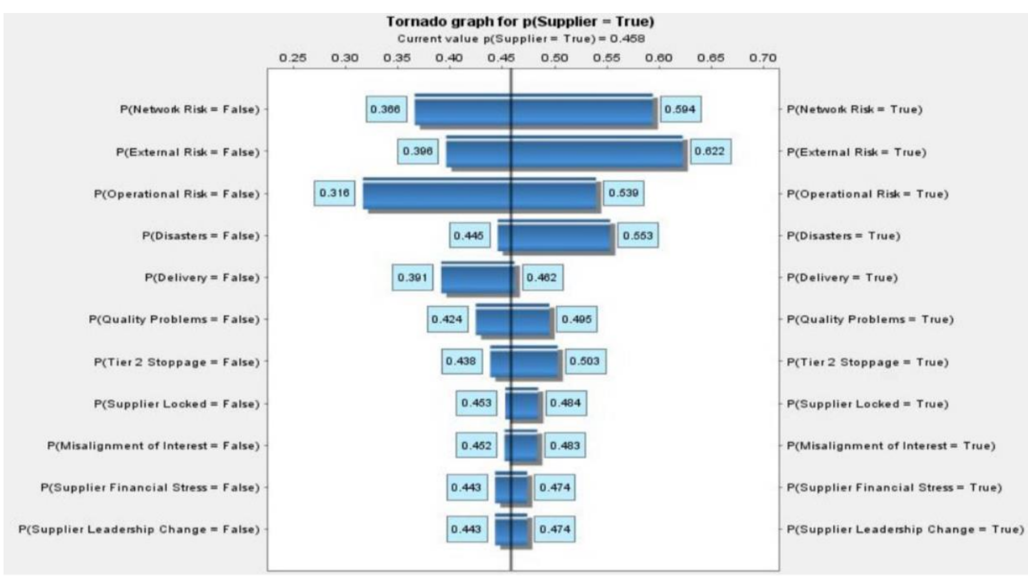


Figure 12: Tornado Graph 2

3.0 Results – Bayesian Model-II

From Bow- Tie Analysis and supplier criticality ranking, based on the probability of disruption calculated from our Bayesian Network analysis, Supplier A and Supplier C have a disruption probability greater than 40%, which as per company standards, they fall in the red zone (risk of extreme failure) hence two mitigation strategies can be adopted by the company to reduce the dependency and risk associated with these suppliers on products which are:

a) Back-up Suppliers- To ensure continuity of goods in case the leading Supplier fails.

b) Multiple Suppliers- Instead of depending on a single supplier, which will become a single point of failure, it is better to distribute our requirements across multiple suppliers. For both mitigation strategies, we need to evaluate the new suppliers before onboarding them quantitatively; for this purpose, we have formulated a Bayesian network based on the factors described in the second Bayesian Analysis.

c) Terminating the relationship with the High-Risk Supplier

So, for implementing these mitigation techniques, we need a new tool to evaluate new suppliers for onboarding them; the results obtained from the second Bayesian network analysis are depicted below: in Fig 13, we can tell the Supplier doesn’t get affected much by the environmental changes as the output of green criteria is 73% True which is comparatively higher than that of resilience and primary Criteria. The absorptive capacity of the Supplier is also not that high because we can say that during many covid companies could not adapt to unexpected situations like Covid-. In primary criteria quality of products from the Supplier is higher and there are delays in the delivery of the raw materials.

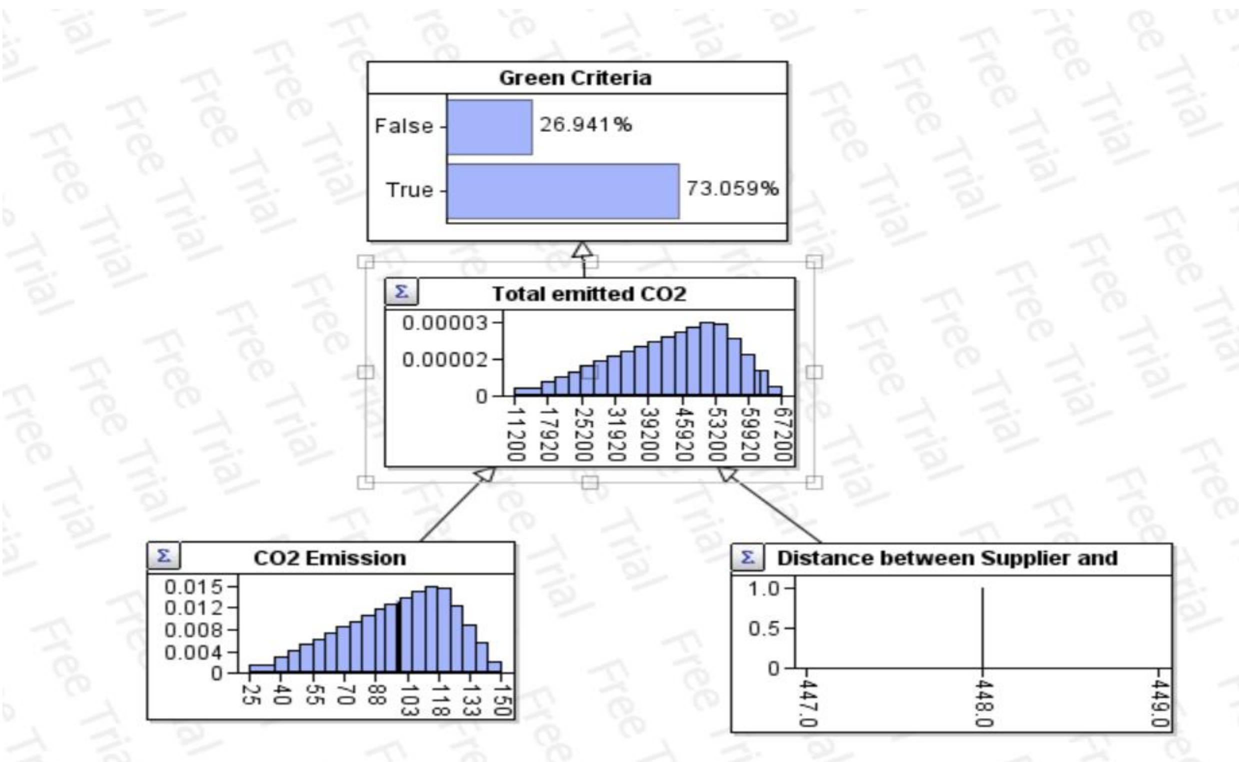


Figure 13: Bayesian Network Analysis Green Criteria

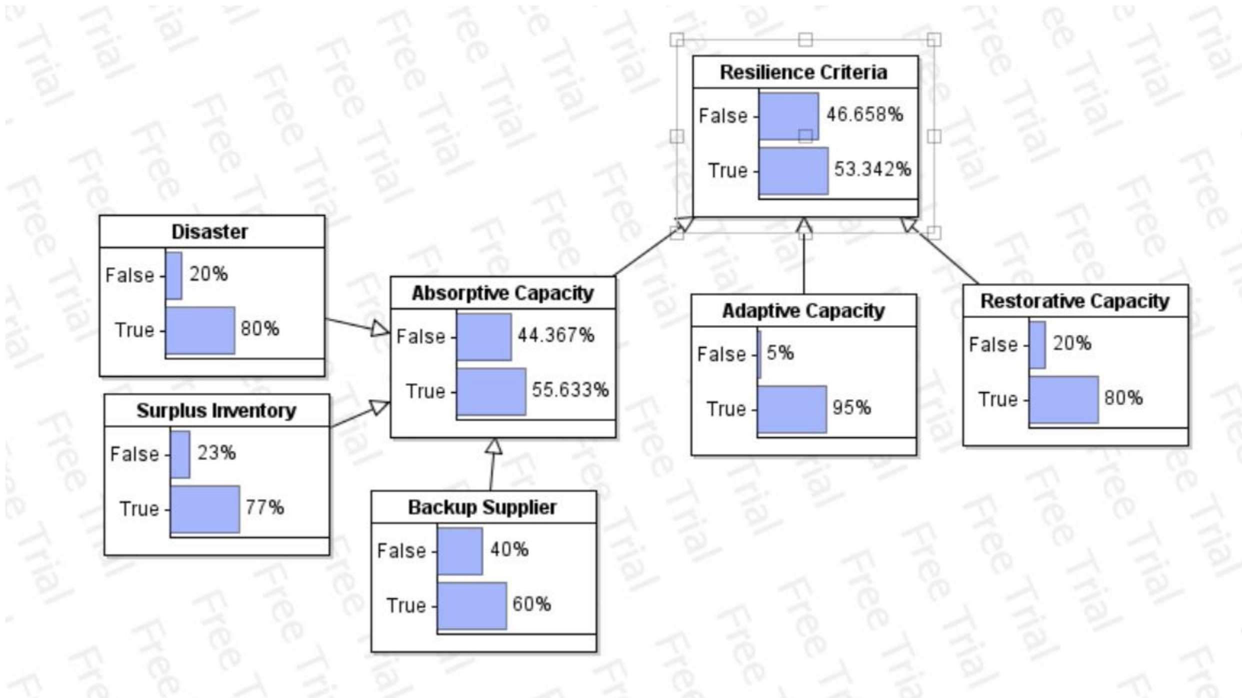


Figure 14: Bayesian Analysis of Resilience Criteria

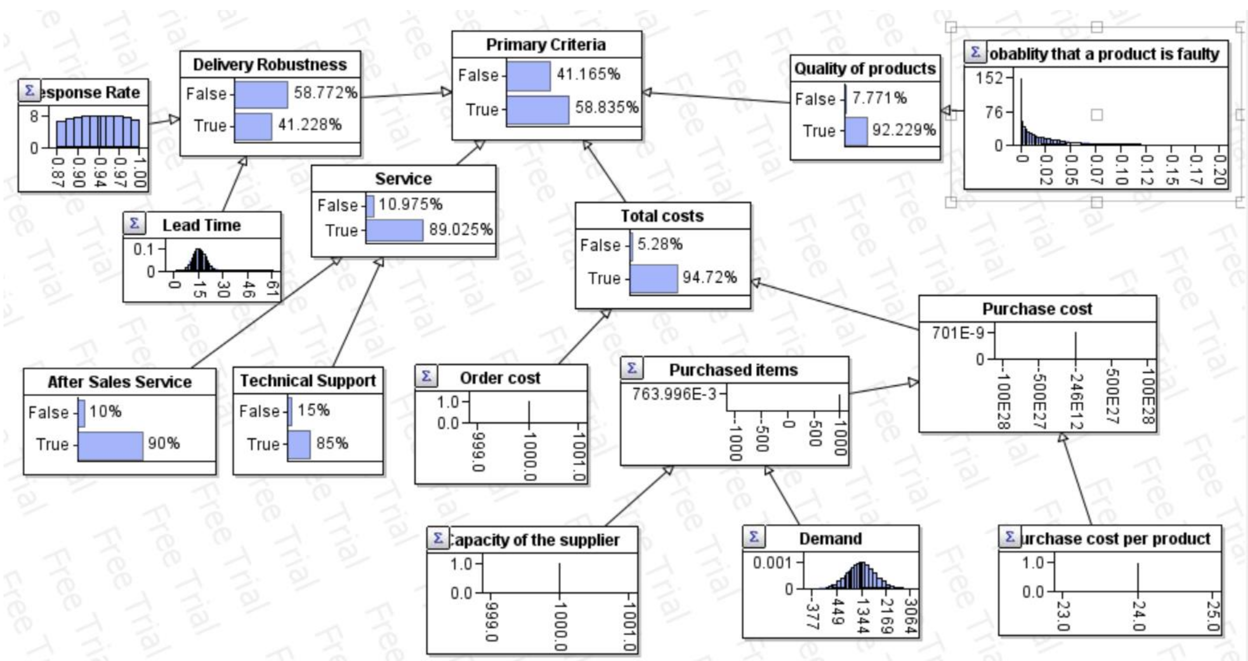


Figure 15: Bayesian Analysis of Primary Criteria

4.0 Conclusion

After careful evaluation of various factors or hazards of delay in production, our model concluded that suppliers are one of the riskiest components in the model of the automobile manufacturer; hence this model focuses on how choosing the right supplier is important and how it may risk the supply chain system of the buyer organization of the manufacturer. Hence, the fault tree analysis and cut set analysis was used to narrow down the factors that may increase the risk component of the supplier, and Bayesian network analysis was analyzed to find the causes in further detail.

Using the Bayesian network developed to calculate each supplier's disruption probability, we observed that the weights assigned to each factor were logical as we divided the impact among the supplier into three classes, with three being the most critical. In our Analysis, only disaster was classified with a weight of 3 because it can disrupt the entire facility. From tornado graphs, we can conclude the validity of these factors as we can see that disaster has the most significant impact and leadership has the most negligible impact. We also observed that this method could quantitatively evaluate the supplier's inability to meet demand. Thus, these methods can be used as a proactive tool to manage supply chain risk; by developing risk profiles for each supplier, we can decide the correct way to deal with the situation by implementing the three possible mitigation techniques discussed that is: Supplier termination, Backup supplier and Multiple suppliers.

The second Bayesian Network analysis created is focused on a new way to evaluate new suppliers. In our Analysis, we are considering three primary factors, resilience and green risk. The concept of measuring the resiliency of suppliers is used sparingly in traditional tools, and recent events have shown us that resiliency (absorptive, adaptive, and restorative ability) should be considered a significant factor. From this Analysis, we can see the advantages of the Bayesian model over traditional tools, such as the ability to factor in non-tangible factors in a quantitative manner. We also demonstrated the powerfulness of the Bayesian model in handling different distributions and different variables (Boolean, constant, discrete, and continuous), also able to include uncertainty factor (leakage factor in noisyor). Furthermore, also developed tool is very flexible as various scenarios can be incorporated easily and will thus provide a much better picture of each supplier under both extreme and normal operating conditions. However, we did observe one major disadvantage: the bayesian network's complexity increases rapidly as more factors are considered.

5.0 List of Abbreviations

SA	Supplier A
SB	Supplier B
SC	Supplier C
SD	Supplier D
SE	Supplier E
SC1	Sub Component 1
SC2	Sub Component 2
SC3	Sub Component 3

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