Cost and Benefit Analysis of Supplier Risk Mitigation in an Aerospace Supply Chain

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***Abstract*—Risk identification and risk estimation are important stages of any risk management process. Existing research in Supply chain risk management has mainly focused on these two stages whereas risk evaluation has not been fully explored which is an equally significant stage involving evaluation of different risk mitigation strategies. The main purpose of this paper is to propose a method of evaluating different mitigation strategies through cost and benefit analysis. The proposed method introduces a unique concept of integrating cost and relative impact of different combinations of mitigation strategies within a network setting of interconnected risk triggers, risk factors and risk mitigation strategies. We have applied our method on a case study that was conducted in an aerospace supply chain. Our approach is useful in identifying an optimal combination of mitigation strategies against a given budget constraint. Furthermore, the model can also be used for determining such strategies in relation to a given level of risk exposure. We have incorporated NoisyOR function within the Bayesian Network model in order to reduce the complexity involved in eliciting a huge number of conditional probability values.**

Keywords—Supply chain risk management; risk evaluation; risk mitigation strategies; NoisyOR function

I. Introduction

Risk management is an established field in some areas of organizational life like finance but it is still a developing theme within the realm of supply chain management [1]. There is a consensus among researchers on treating risk management as a process comprising three stages of risk identification, risk estimation and risk evaluation [2].

Supply Chain Risk Management (SCRM) is defined as "the management of supply chain risks through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity" [3]. Supply chain risks can be viewed with respect to three broad perspectives; a 'butterfly' concept that segregates the causes, risk events and the ultimate impact, the categorization of risks with respect to the resulting impact in terms of delays and disruptions and network based classification in terms of local-and-global causes and local-and-global effects [4].

It is important to realize that risk exists at various levels, inside the focal company and at the network level. Furthermore, risk evaluation depends on the stakeholder's perspective and therefore, the subjective judgement of a particular stakeholder determines what constitutes a risk and what level of risk is acceptable [5].

Bayesian Belief Network (BBN) is a probabilistic graphical model that represents causal relationship between variables and captures uncertainty in dependency in terms of conditional probabilities [6, 7]. BBNs have been used in modelling supply chain risks and found to be an effective technique, however, the scope of such models has been limited to focused areas like supplier selection, risk profiling, etc. [8-10]. We make use of the BBNs in capturing interdependency between supply chain risks and modelling the interaction of mitigation strategies with associated risks taking into account the relative cost and benefit of such strategies. As the number of conditional probability values grows exponentially with the increase in number of causal factors for a risk, we utilize the concept of NoisyOR function in order to reduce the number of values from exponential to linear.

Research Problem and Contribution

Existing research in SCRM has mainly focused on the first two stages of risk management process; risk identification and risk estimation. In general, risk mitigation strategies have been described qualitatively and no study has investigated evaluation of risk mitigation strategies within a network setting of interconnected risks, triggers, consequences and mitigation strategies on the basis of cost and benefit analysis. This research paper is a first step towards bridging this major research gap. It attempts to propose a method that can help researchers and practitioners appreciate the importance of risk evaluation and develop better models for managing supply chain risks.

Outline

Literature review is briefly presented in Section II. BBNs and NoisyOR function are described in Section III. Section IV describes our proposed method of evaluating control strategies followed by its demonstration as a Case Study in Section V. Results and managerial implications are discussed in Section

VI followed by the conclusion and future research presented in Section VII.

II. Literature Review

Risk has been defined as a chance of danger, damage, loss, injury or any other undesired consequences [11]. According to Knight [12], risk is something measurable in a way that probabilities of the outcomes can be estimated whereas, uncertainty is not quantifiable and probabilities of the possible outcomes are not known. According to Jüttner et al. [13], "SCRM aims to identify the potential sources of supply chain risks and implement appropriate actions to avoid or contain supply chain vulnerability". Vulnerability is defined as an exposure to serious disturbances from risks within the Supply Chain as well as risks external to the Supply Chain [14].

Simulation has been extensively used by researchers in modelling supply chain risks. Simulation techniques used in the realm of SCRM include agent-based modelling [15], Monte Carlo simulation [16, 17], discrete event simulation [18], system dynamics modelling [19] and Petri-Net simulation [20]. Generally, the existing studies have either focused on addressing a specific problem or considered risks as independent factors. Risk mitigation strategies have not been evaluated within the network of interconnected risks and strategies and therefore, existing models fail to capture a holistic account of all three stages of risk management process incorporating interdependence between all factors.

Many researchers have proposed proactive mitigation strategies while limited studies have focused on reactive strategies [21-24]. Wieland [25] developed mathematical models for determining optimal solution and break-even points in the realm of four strategies-agility, robustness, resilience and rigidity. Multi-criteria decision making [26, 27] and stochastic programming [28-31] have also been utilized for assessing supply chain risks.

According to Johnson [32], capacity risks can be reduced by outsourcing and building a flexible web of partners whereas, operational hedging can help in reducing currency and political risks. Christopher and Lee [3] proposed strategies of information accuracy, visibility, accessibility and responsive corrective actions. Zsidisin et al. [33] recommended implementation of supplier improvement programs and mitigation of supply disruptions through creating business interruption plans, developing demand forecasts and modelling supply processes. Blackhurst et al. [34] emphasized the significance of real-time sharing of correct information from every node in the supply chain and predicting capacity bottlenecks in global transportation networks. According to Kleindorfer and Saad [35], approaches used to mitigate disruption risks must fit the characteristics and needs of the underlying environment of the focal supply chain.

Sinha et al. [36] introduced a comprehensive risk management process for mitigating supplier risks in an aerospace supply chain. Their method links risk triggers to corresponding risk factors and helps in identifying risk mitigation strategies, however, they did not consider the cost and benefit associated with implementing these strategies. Tummala and Schoenherr [37] introduced a Supply Chain Risk Management Process (SCRMP) and proposed allocating resources to the important risk factors. They assigned cumulative score to each risk factor on the basis of its probability, impact and risk control cost. However, they did not consider the uncertainty involved in risk mitigation. Furthermore, they did not capture the interdependent nature of strategies, risk triggers and risk factors.

III. Bayesian Belief Networks

BBN is an acyclic directed graphical model comprising nodes representing uncertain variables and arcs indicating causal relationships between variables whereas the strength of dependency is represented by the conditional probability values [6]. BBNs have started gaining the interest of researchers in modelling supply chain risks [38]. BBNs offer a unique feature of modelling risks combining both the statistical data and subjective judgment in case of non-availability of data [39, 40]. Researchers have used the BBNs to model specific domains of supply chain risks and validated these models through case studies. The existing BBN based models in SCRM have mainly focused on evaluating risks on the basis of probabilistic interdependency exclusively; however, it is equally important to consider the loss values corresponding to different risks and the cost and benefit associated with each mitigation strategy and to include all these factors into the model itself. We aim to utilize the efficacy of BBNs in dealing with uncertainties and modelling all three stages of SCRM process.

The number of conditional probability values increases exponentially with the increase in number of parent nodes leading to complexity involved in eliciting these probabilities, therefore, it is important to consider incorporating assumptions in the model in order to cope with this problem. NoisyOR function is a useful tool that simplifies the problem and necessitates eliciting only $n + 1$ parameters where n represents the number of parent nodes of a child node [41].

NoisyOR Function

Let $C_1, C_2, \ldots, C_n$ be binary variables indicating all the causes of a binary risk variable R. Each event $C_i = True$ causes $R = True$ unless an inhibitor prevents it with probability of q_i [42].

$$P(R = False | C_i = True) = q_i \tag{1}$$

Assuming all inhibitors as independent,

$$P(R = False | C_1, C_2, \ldots, C_n) = \prod_{j \in T} q_j \tag{2}$$

where T is the set of indices for variables in the state $'\mathrm{True}'$.

If $P(R = True | C_1 = \cdots = C_n = False) > 0$, then leak factor can be incorporated into the model representing a background event that is always on.

IV. Proposed Method

Our proposed method is a first step towards integrating the three stages of SCRM process within the modelling framework of BBNs. We do not follow the process flow of a supply chain as it might not be feasible to model a huge network. The method comprises three main stages of problem structuring, instantiation and inference as shown in Fig. 1.

Problem Structuring

This stage comprises important steps of identifying key supply chain risks, associated risk triggers and mitigation strategies, developing the network structure and expressing nodes as statistical variables. The problem owner needs to ensure that the model is developed to represent the real problem. Furthermore, the model builder can assist in structuring the model keeping in view the mechanics of a BBN.

Instantiation

This stage involves evaluation of (conditional) probabilities either through elicitation from the experts or extraction from the data. Probability elicitation is the most difficult task of the modelling process as the experts find it challenging to describe the conditional probabilities. As the values grow exponentially with the increase in number of parents of a child node, therefore, we introduce the NoisyOR function in order to reduce the number of such values from exponential to linear. In this stage, the loss corresponding to each risk trigger is also ascertained followed by the evaluation of cost associated with different mitigation strategies.

Inference

In this stage, key risk triggers are identified after propagating conditional probability and loss values across the interconnected risk factors, triggers and mitigation strategies. The values from the network are exported to Microsoft Excel for conducting cost and benefit analysis of various combinations of mitigation strategies. Depending on the risk tolerance of the stakeholder, appropriate strategies are selected for implementation.

V. Case Study

We apply our proposed method on a case study presented by Sinha et al. [36]. They had applied their methodology on an aerospace supplier specializing in machined parts. After identifying key risk factors for the supplier and using the failure modes and effects analysis (FMEA), they were able to determine potential failure modes and recommend corrective actions. We have transformed their FMEA representation into risk factors, triggers and mitigation strategies as shown in Table I. Conditional probability values for risk triggers and risk factors are shown in Appendix A whereas loss values for risk triggers and costs associated with different mitigation strategies are presented in Appendices B and C respectively. In contrast to the use of ordinal scales for occurrence and severity in FMEA, we make use of the probability and loss values in our model. Therefore, we have mapped the values for occurrence and severity used in the case study [36] to the parameters of probability and loss respectively. Furthermore, as the case study [36] had not considered the uncertainty associated with the interaction between risk triggers and risks, we have assumed the values for quantification of the NoisyOR function.

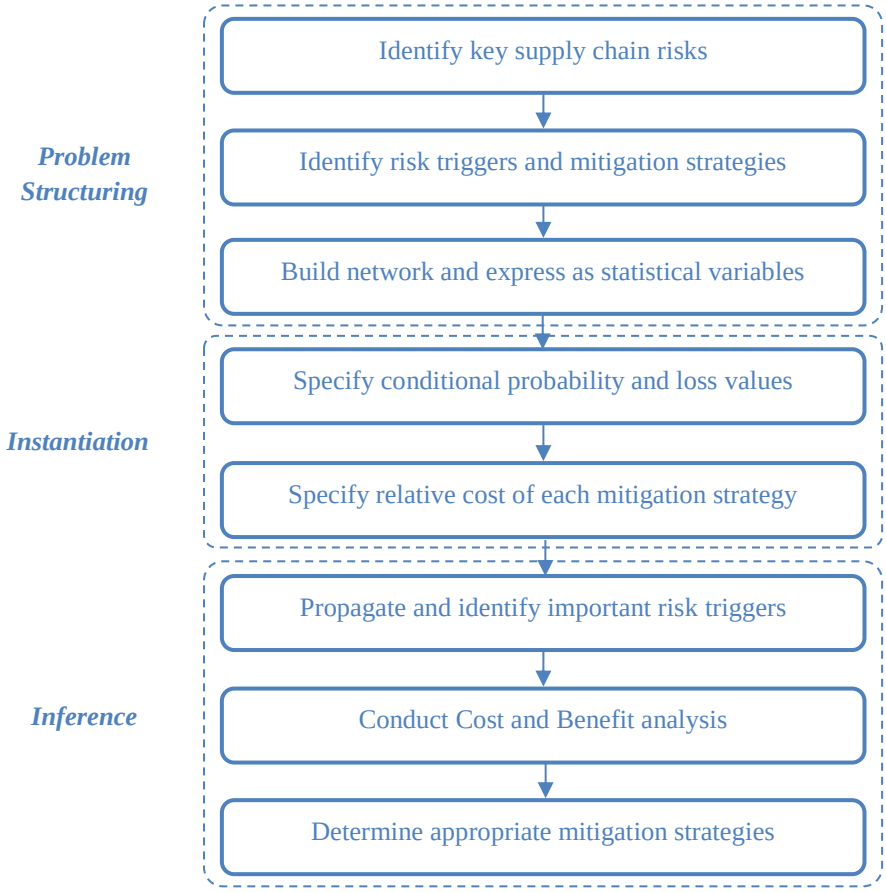

Fig. 1. Cost and benefit based method of evaluating risk mitigation strategies.

TABLE I. RISK FACTORS, RISK TRIGGERS AND MITIGATION STRATEGIES (ADAPTED FROM [36])

Risk Factor	Risk Trigger	Mitigation Strategy
Failure to deliver on time (R1)	Machine breakdown (T1) Non-availability of raw material (T2) Labour problems (T3) Improperly trained workers (T4) Natural calamity at vendor's place (T5) Failure to communicate (T6)	Effective maintenance (M1) Visibility of demand to vendor (M2) Proper company culture (M3) Training (M4) Communication tools (M5)
Poor quality of incoming material (R2)	Low quality material used at vendor's facilities (T7) Improper process at the vendor's end (T8) Insufficient use of quality tools (T9) Improperly trained workers (T4)	Selecting the right quality material (M6) Supplier assessment (M7) Using correct quality programs (M8) Training (M4)
Eroding market share (R3)	No clear market perception (T10) Poor after-service network (T11) Not using the latest technology (T12) High product cost (T13)	Mass customization (M9) Good contact with customer (M10) Implementing the best technology (M11) As per prevailing market conditions (M12)

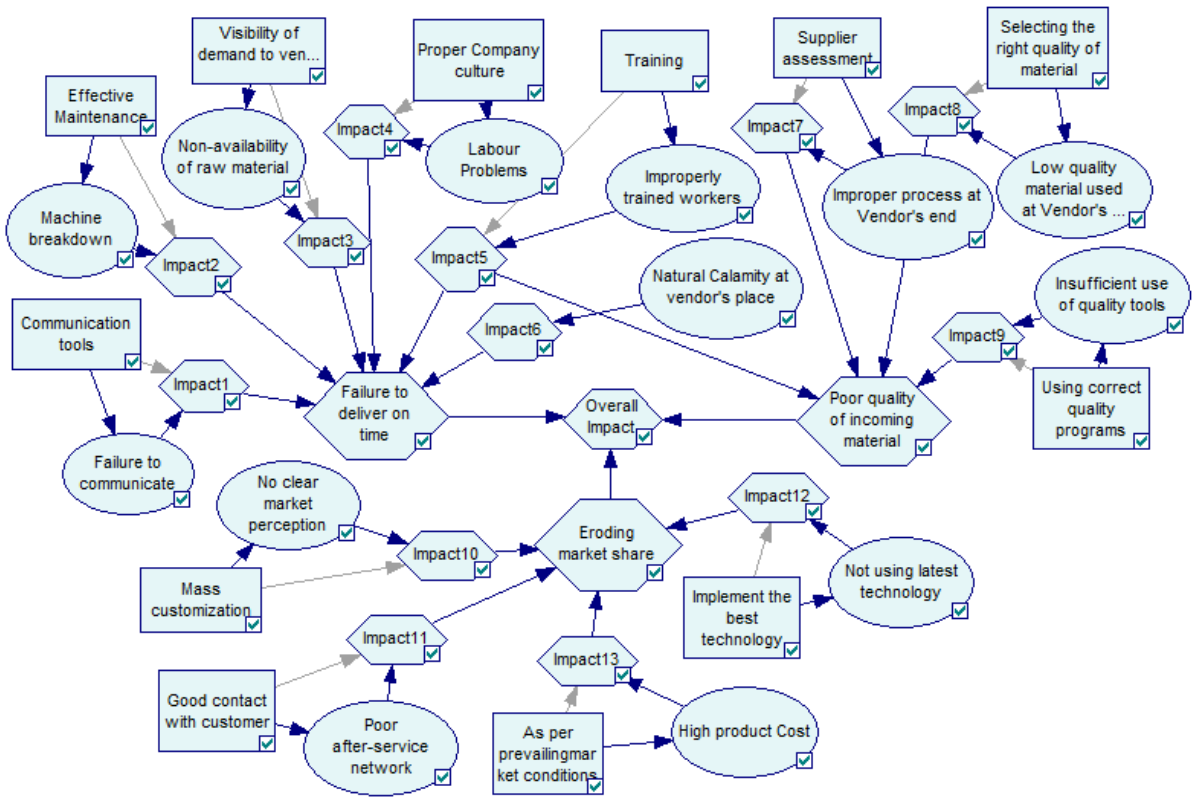

Fig. 2. Risk factors, risk triggers and mitigation strategies modelled as a BBN.

BBN based model was developed in GeNIe [43] as shown in Fig. 2. Each mitigation strategy appears as a rectangular node having binary states of 'Yes (Y)' and 'No (N)'. Each risk factor/trigger is represented by an oval node having binary states of 'True (T)' and 'False (F)'. Risk exposure of each trigger is represented by a diamond node. Risk exposure values of all the triggers corresponding to each risk factor are aggregated through NosiyOR function and finally, the overall risk exposure is calculated through aggregating risk exposure values across all three risk factors.

VI. RESULTS AND DISCUSSION

Once the Bayesian network was updated, risk exposure values for the risk triggers were evaluated as shown in Table II. 'No clear market perception' proved to be the most significant risk trigger and keeping in view the low probability and loss values associated with 'Natural calamity at vendor's place', its risk exposure was insignificant. 'Machine breakdown' was also an important trigger having a high value of risk exposure.

Array of loss exposure values corresponding to different combinations of mitigation strategies was exported to Microsoft Excel. Furthermore, another array of costs associated with these strategies was generated in GeNIe and subsequently exported to Microsoft Excel. The resulting graph representing cost and benefit analysis of different combinations of mitigation strategies is shown in Fig. 3. Data points displayed in blue colour represent the variation in risk exposure with that of the cost associated with different strategies. It is important to note that there is a substantial decrease in risk exposure with slight increase in mitigation cost, however, the rate of this decrement reduces with an increase in mitigation cost. Data points displayed in red colour indicate the improvement in risk exposure incorporating the cost of implementing strategies. All such data points having non-negative values can be considered as appropriate combinations of strategies from the perspective of a risk-neutral decision maker because we have considered expected values in our model.

TABLE II. RISK EXPOSURE VALUES FOR RISK TRIGGERS

Risk Trigger	Risk Exposure
Machine breakdown	51.98
Non-availability of raw material	9.9
Labour problems	0.44
Improperly trained workers	18.7
Natural calamity at vendor's place	0.01
Failure to communicate	24.75
Low quality material used at vendor's facilities	5.45
Improper process at the vendor's end	31.35
Insufficient use of quality tools	16.5
Improperly trained workers	18.7
No clear market perception	97.01
Poor after-service network	21.24
Not using the latest technology	46.2
High product cost	13.2

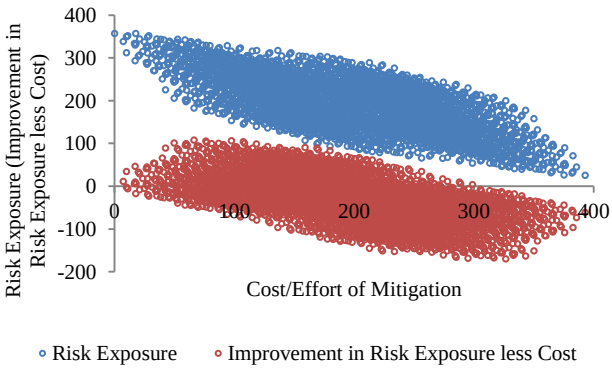

Fig. 3. Cost and benefit analysis of various combinations of mitigation strategies.

It is also important to differentiate between the optimal and inefficient combinations of strategies. Depending on risk tolerance of the stakeholder, specific levels of risk exposure can be achieved through implementing cost-effective mitigation strategies as shown in Fig. 4. For each level of risk exposure, there are a number of possible combinations of strategies, however, there is a unique cost-efficient combination represented by the lowest value.

The model can also be used to segregate risk mitigation strategies on the basis of controllability. It might be difficult to monitor certain mitigation strategies if these are not directly implemented by the stakeholder. 'Using correct quality programs' and 'selecting the right quality material' are examples of such strategies that may not be easily monitored by the stakeholder. Therefore, we explored evaluating other combinations of strategies after setting the states of these two strategies as 'No'. As the two strategies have been eliminated from consideration, there are a total of 1024 combinations for further analysis. Combination of strategies implemented at a cost of 66.22 units results in the maximum net improvement in risk exposure of 108.24 units as shown in Fig. 5. Corresponding combination of strategies is shown in Table III.

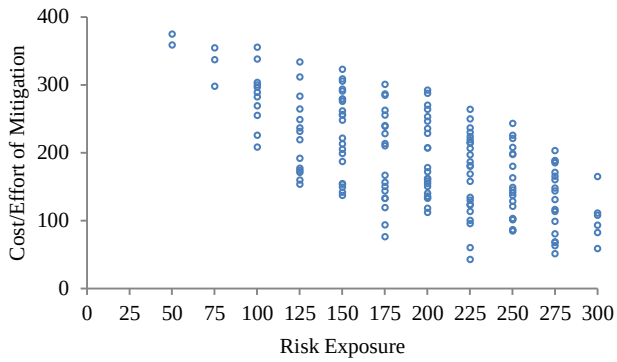

Fig. 4. Optimal combination of strategies for specific level of risk exposure.

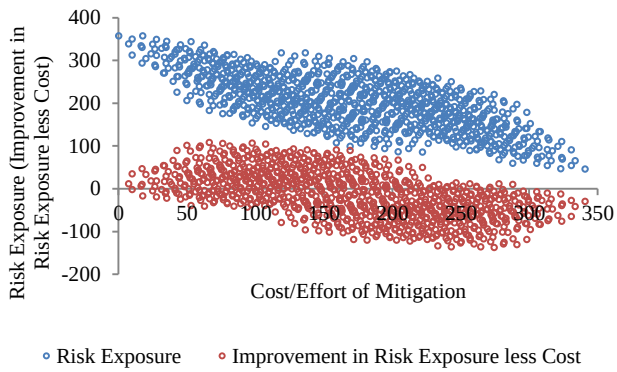

Fig. 5. Cost and benefit analysis of various combinations of mitigation strategies (after prioritizing strategies).

TABLE III. OPTIMAL COMBINATION OF STRATEGIES

Mitigation Strategy	Implement
Effective maintenance	No
Visibility of demand to vendor	No
Proper company culture	No
Communication tools	Yes
Selecting the right quality material	No
Supplier assessment	No
Using correct quality programs	No
Training	No
Mass customization	Yes
Good contact with customer	Yes
Implementing the best technology	No
As per prevailing market conditions	No

Managerial Implications

This technique can help managers appreciate the impact of key risk triggers on associated risks and evaluate cost-effective mitigation strategies in accordance with their risk tolerance. The proposed method not only helps in identifying key risk factors and assessing risk exposure of a network comprising interacting risk factors, triggers and mitigation strategies but also presents a unique concept of evaluating different risk mitigation strategies through demonstrating cost and benefit analysis. One of the main merits of this tool relates to differentiating optimal combination of strategies from other inefficient combinations. Managers can take informed decisions taking into account the interdependent nature of risks and mitigation strategies.

VII. Conclusion

Existing research in the field of SCRM has not fully explored risk evaluation stage of the risk management process. Specifically, the costs and benefits associated with various combinations of risk mitigation strategies have never been investigated. We have introduced a new modelling approach of determining cost-effective combinations of mitigation strategies taking into account the impact of these strategies across the risk triggers and risk factors. We illustrated our approach through simulating an existing case study and demonstrated its efficacy through conducting cost and benefit analysis. BBN based modelling helped capturing the involved uncertainty and the complexity associated with eliciting a large number of conditional probabilities was tackled through incorporating NoisyOR function within the model.

The proposed approach is an important contribution in terms of introducing a new concept of evaluating risk mitigation strategies. The results clearly provided an insight into realizing the importance of adopting such an approach as implementation of mitigation strategies without performing a rigorous analysis would lead to inefficient outcomes. The process can also be used to select an optimal combination of strategies against a target level of risk exposure. The presented technique will help researchers and practitioners in developing and using efficient models of mitigating supply chain risks respectively.

Though the technique has been illustrated through simulating an existing case study, nonetheless, it needs testing in real case studies in order to appreciate the associated challenges. Furthermore, in case of a huge network with many potential strategies, it might not be feasible to conduct cost and benefit analysis of all combinations of control strategies because of computational complexity. However, it will still be possible to evaluate the optimal combination through treating the clusters of risk triggers and interconnected risk factors as independent.

Appendix A. Conditional Probability Values

$$P(T_i = True|M_i)$$

M1	M2	M3	M4	M5	T1	T2	T3	T4	T5	T6
Y					0.1					
N					0.75					
	Y					0.05				
	N					0.25				
		Y					1e-05			
		N					0.01			
			Y					0.001		
			N					0.5		
									0.01	
				Y						0.05
				N						0.75

M6	M7	M8	T7	T8	T9
Y			0.01		
N			0.25		
	Y			0.04	
	N			0.75	
		Y			0.05
		N			0.5

M9	M10	M11	M12	T10	T11	T12	T13
Y				0.1			
N				0.99			
	Y				0.1		
	N				0.99		
		Y				0.0001	
		N				0.75	
			Y				0.0001
			N				0.5

$$P(R_i|T_i = True)$$

R1	T1	T2	T3	T4	T5	T6	Leak Factor
T	0.9	0.9	0.8	0.85	0.99	0.75	0.01
F	0.1	0.1	0.2	0.15	0.01	0.25	0.99

R2	T4	T7	T8	T9	Leak Factor
T	0.95	0.99	0.95	0.75	0.05
F	0.05	0.01	0.05	0.25	0.95

R3	T10	T11	T12	T13	Leak Factor
T	0.99	0.65	0.8	0.8	0.05
F	0.01	0.35	0.2	0.2	0.95

APPENDIX B. LOSS VALUES OF RISK TRIGGERS

Risk Trigger	Loss
Machine breakdown	77
Non-availability of raw material	44
Labour problems	55
Improperly trained workers	44
Natural calamity at vendor's place	1
Failure to communicate	44
Low quality material used at vendor's facilities	22
Improper process at the vendor's end	44
Insufficient use of quality tools	44
No clear market perception	99
Poor after-service network	33
Not using the latest technology	77
High product cost	33

APPENDIX C. COST OF MITIGATION STRATEGIES

Mitigation Strategy	Cost
Effective maintenance	11
Visibility of demand to vendor	11
Proper company culture	22
Communication tools	22
Selecting the right quality material	11
Supplier assessment	33
Using correct quality programs	55
Training	66
Mass customization	33
Good contact with customer	11
Implementing the best technology	77
As per prevailing market conditions	44

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