Chapter 2
Cost-Effectiveness and Manageability Based Prioritisation of Supply Chain Risk Mitigation Strategies

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Abstract Risk treatment is an important stage of the risk management process involving selection of appropriate strategies for mitigating critical risks. Limited studies have considered evaluating such strategies within a setting of interdependent supply chain risks and risk mitigation strategies. However, the selection of strategies has not been explored from the perspective of manageability-the ease of implementing and managing a strategy. We introduce a new method of prioritising strategies on the basis of associated cost, effectiveness and manageability within a theoretically grounded framework of Bayesian Belief Networks and demonstrate its application through a simulation study. The proposed approach can help managers select an optimal combination of strategies taking into account the effort involved in implementing and managing such strategies. The results clearly reveal the importance of considering manageability in addition to cost-effectiveness within a decision problem of ranking supply chain risk mitigation strategies.

2.1 Introduction

Risk management involves important stages of risk identification, risk analysis, risk evaluation, risk treatment and risk monitoring (SA 2009). Supply chain risk management (SCRM) is gaining an increasing interest both from the researchers and practitioners (Sodhi et al. 2012). Complex interactions between supply chain risks ranging across the entire spectrum of a supply network make it a challenging task to identify, assess and manage key risks. Limited studies have focused on exploring causal interactions between supply chain risks (Badurdeen et al. 2014; Garvey et al. 2015)

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and integrating the impact of risk mitigation strategies on associated risks within the modelling framework (Aqlan and Lam 2015). However, to the best of our knowledge, no attempt has been made to capture the manageability associated with implementing a mitigation strategy within the modelling framework. Manageability relates to the concept of ease involved in managing a strategy. Besides capturing the manageability of risks (effectiveness of strategies) representing the potential for reducing the risk (Aven et al. 2007), we propose integrating the cost and manageability of mitigation strategies within a theoretically grounded framework of Bayesian Belief Networks (BBNs) encompassing complex interactions between risks and strategies.

BBN is a directed acyclic graph comprising nodes representing uncertain variables and arcs indicating causal relationships between variables whereas the strength of dependency is represented by the conditional probability values. BBNs offer a unique feature of modelling risks combining both the statistical data and subjective judgment in case of non-availability of data (Qazi et al. 2014). In the last years, BBNs have also started gaining the interest of researchers in modelling supply chain risks (Badurdeen et al. 2014).

In this chapter, we aim to address the decision problem of prioritising risk mitigation strategies considering the cost, effectiveness and manageability of such strategies within an interconnected network of interacting supply chain risks and strategies. The proposed method is deemed as contribution to the literature on Risk Management in general and SCRM in particular. Existing models focusing on cost-effectiveness of strategies assume the same level of manageability for all strategies.

The remainder of the chapter is organised as follows: A brief review of the relevant literature is presented in Sect. 2.2. The modelling approach of prioritising risk mitigation strategies is described in Sect. 2.3 and demonstrated through a simulation study in Sect. 2.4. Results and managerial implications are also described in Sect. 2.4. Finally, key findings and future research agenda are presented in Sect. 2.5.

2.2 Literature Review

SCRM is gaining interest of researchers and practitioners because of the occurrence of major supply chain disruptions (Sodhi et al. 2012). Global sourcing and lean operations are the main drivers of supply chain disruptions (Son and Orchard 2013). The likelihood of the occurrence of an (undesirable) event, and the negative implications of the event are the two common measures of risk (Bogataj and Bogataj 2007). Risk mitigation strategies are implemented in order to reduce the likelihood of occurrence and/or negative impact of risks (Tang and Tomlin 2008). Robust strategies must be developed in order to help firms reduce cost and/or improve customer satisfaction under normal conditions and to enable firms sustain operations during and after a disruption (Tang 2006).

According to Johnson (2001), 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 (2004) proposed a number of strategies including information accuracy, visibility, accessibility and responsive corrective actions. Zsidisin et al. (2004) recommended implementation of supplier improvement programs and mitigation of supply disruptions through creating business interruption plans, developing demand forecasts and modelling supply processes.

Using the interpretive structural modelling, Faisal et al. (2006) introduced an approach of understanding dynamics between different enablers of risk mitigation. A similar concept of establishing cause and effect relationships between the enablers of risk mitigation was explored in the Electronic supply chain in order to determine the main drivers (Rajesh and Ravi 2015). Using a multi-method approach, Speier et al. (2011) introduced a framework to examine the threat of potential disruptions on supply chain processes and identified suitable potential mitigation strategies under different conditions. Christopher et al. (2011) used a multiple case study approach in several industries to understand how managers assess and mitigate global sourcing risks across the entire supply chain. They proposed four generic strategies including network re-engineering, collaboration, agility and risk management culture for managing global sourcing risk. Son and Orchard (2013) developed an analytical model for examining the effectiveness of two inventory based policies for mitigating the impact of supply-side disruptions in a supply chain.

The main limitation of existing studies is their limited focus on capturing interdependency between supply chain risks and mitigation strategies. Keeping in view the significance of modelling systemic risks and capturing non-linear complex interactions (Ackermann et al. 2014), researchers have started modelling interdependency between supply chain risks (Badurdeen et al. 2014; Garvey et al. 2015). However, to the best of our knowledge, interdependency between risks and risk mitigation strategies has not been explored within a probabilistic network setting including cost, effectiveness and manageability of strategies. Qazi et al. (2015b) introduced a model for prioritising strategies within a probabilistic network of interacting risks and strategies. In order to capture the risk appetite of a decision maker, Qazi et al. (2015c) proposed an expected utility based method to select optimal strategies. In this chapter, we integrate cost, effectiveness and manageability of strategies within a single model and focus on a different problem where the main purpose is to prioritise specific number of strategies instead of optimising a portfolio of strategies subject to a budget constraint.

BBNs present a useful technique for capturing interaction between risk events and performance measures (Badurdeen et al. 2014). Another advantage of using BBNs for modelling supply chain risks is their ability of back propagation that helps in determining the probability of an event that may not be observed directly. BBNs also provide a clear graphical structure that most people find intuitive to understand. Besides, it becomes possible to conduct flexible inference based on partial observations, which allows for reasoning (Onisko 2008). Another important feature of using BBNs is to conduct what-if scenarios (Blodgett and Anderson 2000). There are certain problems associated with the use of BBNs: along with the increase in number of nodes representing supply chain risks, a considerable amount of data is required in populating the network with (conditional) probability values; similarly, there are also computational challenges associated with the increase in number of nodes.

2.3 Proposed Modelling Approach

Based on the efficacy of BBNs in capturing interdependencies between risks, we consider BBN based modelling of a supply network as an effective approach. Such a modelling technique can help managers visualise interaction between supply chain risks and take effective mitigation strategies (Qazi et al. 2014, 2015a). BBNs have already been explored in the literature on SCRM, however, the proposed approach is unique in terms of integrating the cost, effectiveness and manageability of risk mitigation strategies within the network setting of interacting supply chain risks and strategies.

2.3.1 BBNs

BBN is a graphical framework for modelling uncertainty. BBNs have their background in statistics and artificial intelligence and were first introduced in the 1980s for dealing with uncertainty in knowledge-based systems (Sigurdsson et al. 2001). BBNs have been successfully used in addressing problems related to a number of diverse specialties including reliability modelling, medical diagnosis, geographical information systems, and aviation safety management among others. For understanding the mechanics and modelling of BBNs, interested readers may consult Charniak (1991), Sigurdsson et al. (2001), Nadkarni and Shenoy (2001), Nadkarni and Shenoy (2004), Jensen and Nielsen (2007), and Kjaerulff and Anders (2008). A BBN consists of following elements:

- A set of variables (each having a finite set of mutually exclusive events) and a set of directed edges between variables forming a directed acyclic graph; a directed graph is acyclic if there is no directed path $A_1 \rightarrow \cdots \rightarrow A_n$ so that $A_1 = A_n$, furthermore, the directed edges represent statistical relations if the BBN is constructed from the data whereas they represent causal relations if they have been gathered from experts' opinion,
- A conditional probability table $P(X|Y_1, \ldots, Y_n)$ attached to each variable X with parents $Y_1, \ldots, Y_n$.

2.3.1.1 Chain Rule for BBNs

Let a Bayesian Network be specified over $A = \{A_1, \ldots, A_n\}$, the chain rule of probability theory allows factoring joint probabilities resulting in the calculations made under certain probability states. The structure of a BBN implies that the value of a particular node is conditional only on the values of its parent nodes. Therefore, the unique joint probability distribution $P(A)$ representing the product of all conditional probability tables is given as follows:

$$P(A) = \prod_{i=1}^{n} P(A_i | pa(A_i)), \tag{2.1}$$

where $pa(A_i)$ are the parents of A_i.

2.3.2 *Assumptions*

Our model is based on following assumptions:

1. Supply chain risks and corresponding sources are known and these can be modelled as a directed acyclic graph.
2. All random variables and risk mitigation strategies are represented by binary states.
3. Conditional probability values for the risks and associated losses can be elicited from stakeholders and the resulting network represents close approximation to the actual perceived risks and associated interdependency.
4. Cost and manageability associated with each potential risk mitigation strategy are known.
5. All stakeholders within the supply chain are willing to share information about key risks, loss values and effort involved in implementing potential strategies.

2.3.3 *Supply Chain Risk Network*

A discrete supply chain risk network $RN = (X, G, P, L, U, C, C_m)$ is a seven-tuple consisting of [adapted from Kjaerulff and Anders (2008)]:

- a directed acyclic graph (DAG),$G = (V, E)$, with nodes (V) representing discrete risks and risk sources (X_R), discrete risk mitigation strategies (X_S), loss functions (L), utility functions (U), cost functions (C), manageability weighted cost functions (C_m) and directed links (E) encoding dependence relations,
- a set of conditional probability distributions (P) containing a distribution, $P(X_{R_i} | X_{pa(R_i)})$, for each risk and risk source (X_{R_i}),

- a set of loss functions (L) containing one loss function, $l(X_{pa(V)})$, for each node v in the subset $V_l \in V$ of loss nodes,
- a set of utility functions (U) containing one utility function, $u(X_{pa(V)})$, for each node v in the subset $V_u \in V$ of utility nodes,
- a set of cost functions (C) containing one cost function, $c(X_{pa(V)})$, for each node v in the subset $V_c \in V$ of cost nodes,
- a set of manageability weighted cost functions (C_m) containing one manageability weighted cost function, $c_m(X_{pa(V)})$, for each node v in the subset $V_{c_m} \in V$ of manageability weighted cost nodes.

Risk network expected loss, $RNEL(X)$, is given as follows (Qazi et al. 2015b):

$$RNEL(X) = \prod_{X_v \in X_R} P(X_v | X_{pa(v)}) \sum_{w \in V_L} l(X_{pa(w)}) \tag{2.2}$$

Risk network expected utility for loss, $RNEU(X)$, is given as follows (Qazi et al. 2015c):

$$RNEU(X) = \prod_{X_v \in X_R} P(X_v | X_{pa(v)}) \sum_{w \in V_L} u(X_{pa(w)}) \tag{2.3}$$

2.3.3.1 An Illustrative Example of a Simple BBN

We present a very simple BBN comprising three risks; R1, R2 and R3 as shown in Fig. 2.1. Each risk is assumed to have two states: True (T) or False (F). R3 is the parent node influencing two child nodes 'R1' and 'R2' which are the leaf nodes. The (conditional) probability values of the risks are given in Table 2.1. The updated probability value of R1 and R2 can be calculated using Eq. (2.4). One of the benefits of BBNs relates to the revision of beliefs once any evidence is propagated across a variable or set of variables. The posterior belief about R3 can be calculated using Eq. (2.5) once the evidence is instantiated at R1 or R2. The updated probabilities of R1 and R2 are 0.44 and 0.544, respectively as shown in Eqs. (2.6) and (2.7). Similarly, the posterior probabilities of R3 are 0.82 and 0.99 corresponding to the realisation of R1 and R2, respectively as shown in Eqs. (2.8) and (2.9).

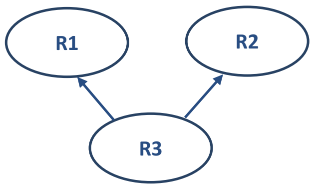

Fig. 2.1 A BBN comprising three variables

Table 2.1 (Conditional) probability values for the three nodes

Parent	$P(Risk\|Parent)$			
	R1		R2	
R3	T	F	T	F
T (0.6)	0.6	0.4	0.9	0.1
F (0.4)	0.2	0.8	0.01	0.99

$$P(Ri = T) = P(Ri = T|R3 = T) * P(R3 = T) + P(Ri = T|R3 = F) * P(R3 = F) \tag{2.4}$$

$$P(R3 = T|Ri = T) = \frac{P(R3 = T, Ri = T)}{P(Ri = T)} = \frac{P(Ri = T|R3 = T) * P(R3 = T)}{P(Ri = T)} \tag{2.5}$$

$$P(R1 = T) = (0.6 * 0.6) + (0.2 * 0.4) = 0.44 \tag{2.6}$$

$$P(R2 = T) = (0.9 * 0.6) + (0.01 * 0.4) = 0.544 \tag{2.7}$$

$$P(R3 = T|R1 = T) = \frac{0.6 * 0.6}{0.44} = 0.82 \tag{2.8}$$

$$P(R3 = T|R2 = T) = \frac{0.9 * 0.6}{0.544} = 0.99 \tag{2.9}$$

In order to calculate $RNEL(X)$ and $RNEU(X)$, we assume the loss and utility values corresponding to different states of risks as shown in Table 2.2 where utility function is considered as $u(loss) = -(loss * loss)$. Using Eqs. (2.10) and (2.11), the expected loss and expected utility values are calculated as 537 and -461428, respectively.

$$\begin{aligned} RNEL(X) = {} & P(R1 = T, R2 = T, R3 = T) * l(R1 = T, R2 = T, R3 = T) \\ & + P(R1 = T, R2 = F, R3 = T) * l(R1 = T, R2 = F, R3 = T) \\ & + P(R1 = T, R2 = T, R3 = F) * l(R1 = T, R2 = T, R3 = F) \\ & + P(R1 = T, R2 = F, R3 = F) * l(R1 = T, R2 = F, R3 = F) \\ & + P(R1 = F, R2 = T, R3 = F) * l(R1 = F, R2 = T, R3 = F) \\ & + P(R1 = F, R2 = T, R3 = T) * l(R1 = F, R2 = T, R3 = T) \\ & + P(R1 = F, R2 = F, R3 = T) * l(R1 = F, R2 = F, R3 = T) \\ & + P(R1 = F, R2 = F, R3 = F) * l(R1 = F, R2 = F, R3 = F) \\ = {} & 537 \end{aligned} \tag{2.10}$$

Table 2.2 Loss and utility values for different states of risks

Risk			Loss (l) (monetary units)	Utility (u) (10^3)
R1	R2	R3		
State				
T	T	T	1000	−1000
T	F	T	750	−562.5
T	T	F	550	−302.5
T	F	F	300	−90
F	T	F	200	−40
F	T	T	700	−490
F	F	T	400	−160
F	F	F	0	0

$$\begin{aligned} RNEU(X) = {} & P(R1 = T, R2 = T, R3 = T) * u(R1 = T, R2 = T, R3 = T) \\ & + P(R1 = T, R2 = F, R3 = T) * u(R1 = T, R2 = F, R3 = T) \\ & + P(R1 = T, R2 = T, R3 = F) * u(R1 = T, R2 = T, R3 = F) \\ & + P(R1 = T, R2 = F, R3 = F) * u(R1 = T, R2 = F, R3 = F) \\ & + P(R1 = F, R2 = T, R3 = F) * u(R1 = F, R2 = T, R3 = F) \\ & + P(R1 = F, R2 = T, R3 = T) * u(R1 = F, R2 = T, R3 = T) \\ & + P(R1 = F, R2 = F, R3 = T) * u(R1 = F, R2 = F, R3 = T) \\ & + P(R1 = F, R2 = F, R3 = F) * u(R1 = F, R2 = F, R3 = F) \\ & = -461428 \end{aligned} \tag{2.11}$$

2.3.4 Problem Statement

Given different options of implementing risk mitigation strategies within a probabilistic network of interconnected supply chain risks and strategies, how do we prioritise these strategies keeping in view the cost, effectiveness and manageability of strategies?

2.3.5 Objective Function

In this chapter, we aim to prioritise risk mitigation strategies yielding maximum weighted summation of normalised expected utility for loss and normalised utility for manageability weighted mitigation cost.

$$\max_{\gamma_{x_s} \in \gamma_{X_S}} w * \overline{RNEU}(X_{\gamma_{x_s}}) + (1 - w) * \overline{U}(C_{m_{\gamma_{x_s}}}), \quad s.t.\ 0 < n \leq N \tag{2.12}$$

where

γ_{X_S} is a set of all possible orderings of different states of n mitigation strategies $(x_{s_1} \times x_{s_2} \times \ldots \times x_{s_n})$,
$\overline{RNEU}(X)$ is the normalised expected utility for loss,
w is the relative importance weighting of normalised expected utility for loss,
$\overline{U}(C_{m_{\gamma_{x_s}}})$ is the normalised utility for manageability weighted cost of implementing γ_{x_s} combination of mitigation strategies,
n is the number of strategies considered for implementation,
N is the maximum number of potential strategies.

In the case of a risk-neutral decision maker (assumed in the simulation study), the objective function transforms as follows:

$$\max_{\gamma_{x_s} \in \gamma_{X_S}} w * \overline{U}(RNEL(X_{\gamma_{x_s}})) + (1 - w) * \overline{U}(C_{m_{\gamma_{x_s}}}), \quad s.t.\ 0 < n \leq N \tag{2.13}$$

where $\overline{U}(RNEL(X))$ is the normalised utility for risk network expected loss.

In order to assign manageability score to the strategies, we propose using the ordinal scale (1–10) shown in Table 2.3.

2.3.6 Modelling Process

The following steps must be followed in developing the proposed network of interacting supply chain risks and mitigation strategies:

1. Define the boundaries of the supply network and identify stakeholders.
2. Identify key risks and potential risk mitigation strategies on the basis of input received from each stakeholder through interviews and/or focus group sessions.
3. Refine the qualitative structure of the resulting network involving all stakeholders.

Table 2.3 Manageability scale for ranking of risk mitigation strategies

Manageability scale	Ease of managing risk mitigation strategy
1–2	Very easy
3–4	Easy
5–6	Neither easy nor difficult
7–8	Difficult
9–10	Very difficult

4. Determine (conditional) probability values, loss values resulting from risks and cost and manageability score associated with implementing each potential mitigation strategy and populate the BBN with all parameters.
5. Run the model for each combination of strategies and determine the expected utility (loss) value.
6. Analyse the results and prioritise risk mitigation strategies on the basis of relative importance of normalised expected utility for loss and normalised utility for manageability weighted cost of strategies.
7. Validate the model output involving stakeholders.

2.4 Simulation Study

We demonstrate the application of our proposed approach through a simple supply network (Garvey et al. 2015) as shown in Fig. 2.2. The model was developed in GeNIe 2.0 (2015). The supply network comprises a raw material source (RM), two manufacturers (M1 and M2), a warehouse (W) and a retailer (R). We also consider a transportation link between the warehouse and retailer (W-R). Risks are represented by nodes comprising bar charts whereas resulting losses and mitigation strategies are represented by diamond and rectangular shaped nodes, respectively. Though each domain of the supply network may comprise a number of risks and corresponding sources, we consider limited risks for the sake of simplicity. Although the presented model represents the process flow of the supply chain, the

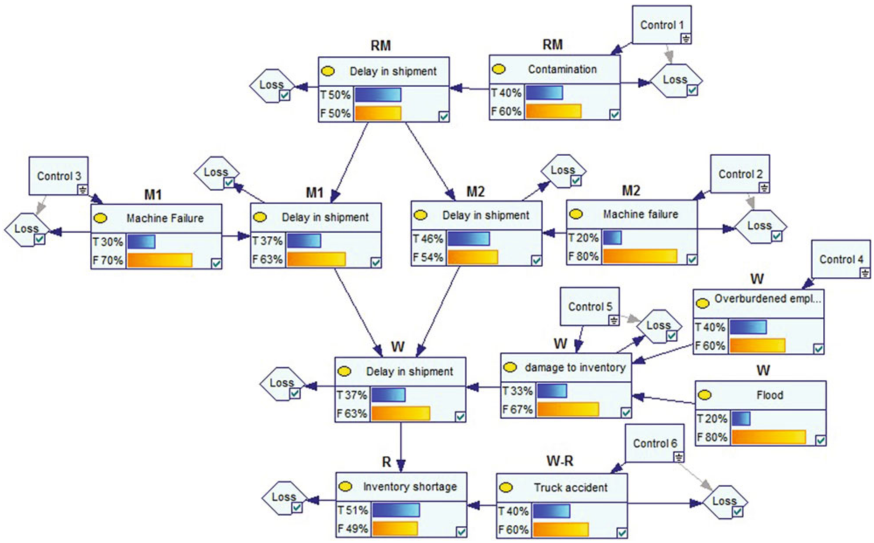

Fig. 2.2 Bayesian network based model of a supply network developed in GeNIe 2.0 (2015) (adapted from Garvey et al. (2015))

Table 2.4 Loss values for different risks

Supply chain element	Risk	Loss (monetary units)
Raw material source	Contamination (R1)	200
	Delay in shipment (R2)	400
Manufacturer-I	Machine failure (R4)	200
	Delay in shipment (R5)	400
Manufacturer-II	Machine failure (R3)	200
	Delay in shipment (R6)	400
Warehouse	Overburdened employee (R7)	–
	Damage to inventory (R8)	500
	Delay in shipment (R9)	600
	Flood (R12)	–
Warehouse to retailer	Truck accident (R10)	500
Retailer	Inventory shortage (R11)	800

proposed approach is not strictly limited to capturing the network configuration of a supply chain as it might not be feasible to model a huge supply network. Therefore, we focus on modelling the risk network instead of mapping the entire supply network.

Each risk and mitigation strategy is represented by binary states of ‘True (T)’ or ‘False (F)’ and ‘Yes’ or ‘No’, respectively. Assumed loss values associated with the risks are shown in Table 2.4. The strength of interdependency between risks and the impact of strategies on related risks are represented by (conditional) probability values as shown in Table 2.5. As R1 does not have a parent node, its probability value is not contingent on any node. The italicised value represents the reduced probability of a risk after implementation of the related strategy. The conditional probability value of R2 (being True) is 0.8 given that its parent node ‘R1’ is in ‘True’ state. Implementation of each mitigation strategy is assumed to incur a cost of 100 units. The assumed manageability scores are shown in Table 2.6. All parameters specific to a real case study can be elicited from experts through interviews and focus group sessions.

2.4.1 Results and Analysis

After populating the model with assumed parameters, it was updated and the array of values corresponding to different combinations of mitigation strategies was exported to a Microsoft Excel worksheet. We evaluated the potential strategies with respect to the cost-effectiveness based ranking scheme followed by the prioritisation of strategies considering both manageability and cost-effectiveness. The results provided an important insight into realising the significance of incorporating manageability aspect into the model and prioritising strategies through the proposed approach.

Table 2.5 (Conditional) probability values [$P(risk = F|parents) = 1 - P(risk = T|parents)$]

Parents				P(risk = T|parents)					
$R1$	$R2$	$R3$	$R4$	$R1$	$R2$	$R3$	$R4$	$R5$	$R6$
				0.4					
				0.1					
T					0.8				
F					0.3				
						0.2			
						0.1			
							0.3		
							0.2		
	T		T					0.7	
	T		F					0.4	
	F		T					0.6	
	F		F					0.1	
	T	T							0.9
	T	F							0.6
	F	T							0.5
	F	F							0.2

Parents							P(risk = T|parents)					
$R5$	$R6$	$R7$	$R8$	$R9$	$R10$	$R12$	$R7$	$R8$	$R9$	$R10$	$R11$	$R12$
							0.4					
							0.3					
		T				T		0.8				
								0.5				
		T				F		0.3				
								0.*15*				
		F				T		0.6				
								0.4				
		F				F		0.2				
								0.15				
T	T		T						0.9			
T	T		F						0.5			
T	F		T						0.6			
T	F		F						0.3			
F	T		T						0.4			
F	T		F						0.3			
F	F		T						0.3			
F	F		F						0.2			
										0.4		
										0.15		
				T	T						0.9	

(continued)

Table 2.5 (continued)

Parents							P(risk = T|parents)					
$R5$	$R6$	$R7$	$R8$	$R9$	$R10$	$R12$	$R7$	$R8$	$R9$	$R10$	$R11$	$R12$
				T	F						0.7	
				F	T						0.6	
				F	F						0.2	
												0.2

Table 2.6 Manageability scores assigned to the risk mitigation strategies

Risk mitigation strategy (control) ID	Strategy	Impact on risk	Manageability score
1	Quality assurance program	R1	10
2	Scheduled maintenance program	R3	1
3	Scheduled maintenance program	R4	2
4	Scheduling software and monitoring program	R7	6
5	Early warning system	R8	5
6	Training on simulator	R10	9

2.4.1.1 Cost-Effectiveness Based Prioritisation of Strategies

We evaluated the cost-effectiveness of strategies and prioritised these through the lens of risk network expected loss as shown in Fig. 2.3. Each point represents one of the 64 different combinations of six mitigation strategies whereas the corresponding value was calculated using Eq. (2.2) for the specific combination of strategies applied to the risk network shown in Fig. 2.2. As each strategy was assumed to incur 100 units of mitigation cost, the strategies represented by the lowest points corresponding to each number of strategies are also the cost-effective strategies. Considering the cost-benefit analysis, strategies resulting in maximum improvement in the risk network expected loss (less mitigation cost) must be selected. Such strategies are represented by the peak points appearing in Fig. 2.4.

It is interesting to note that there is only one cost-effective combination of 5 strategies, however, implementation of all 6 strategies does not result in achieving the net gain. Moreover, the value of net improvement increases up to 2 strategies and declines beyond that point. Optimal strategies are shown in Table 2.7. Strategy 4 is not a feasible strategy except once all the potential strategies need to be implemented.

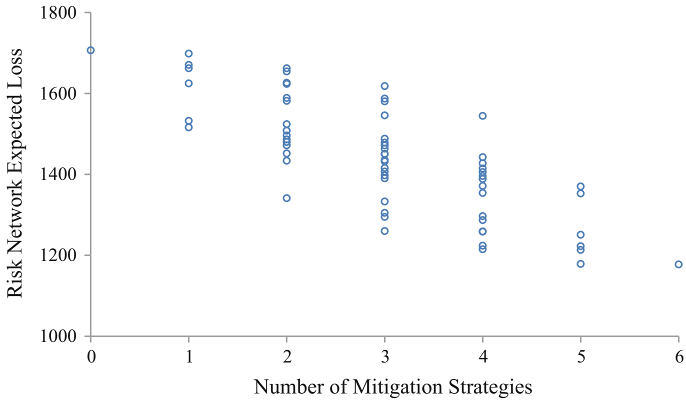

Fig. 2.3 Variation of risk network expected loss with respect to the number of strategies

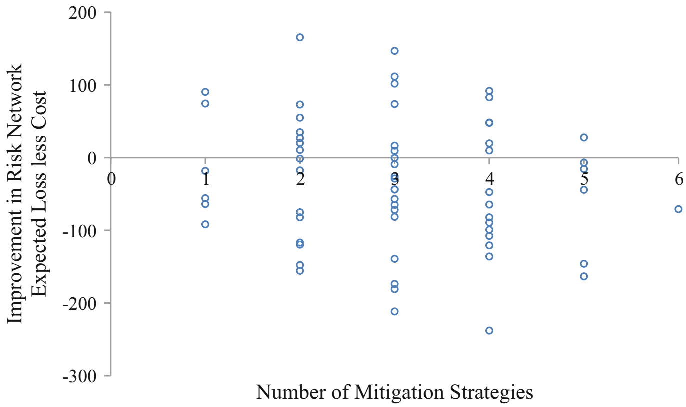

Fig. 2.4 Variation of cost-effectiveness of risk mitigation strategies with respect to the number of strategies

This is mainly because of the fact that the strategy is linked to R7 with no loss value associated with the risk (Table 2.4). Furthermore, R7 does not appear to be a major source of disruption across the entire risk network and even if all 6 strategies are implemented (including Strategy 4), the risk network expected loss is not reduced substantially (Fig. 2.3). That is why, when all 6 strategies are selected, the total cost outweighs the associated benefit.

Table 2.7 Cost-effectiveness based prioritisation of strategies

Number of risk mitigation strategies	Prioritised strategies
1	6
2	1 and 6
3	1, 5 and 6
4	1, 3, 5 and 6
5	All except 4
6	All

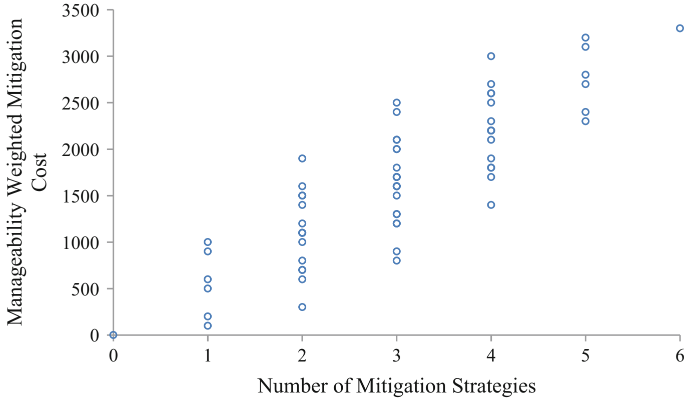

Fig. 2.5 Variation of manageability weighted mitigation cost with respect to the number of strategies

2.4.1.2 Manageability and Cost-Effectiveness Based Prioritisation of Strategies

We prioritised the strategies on the basis of associated manageability, cost and effectiveness. Values of manageability weighted cost corresponding to different combinations of strategies are depicted in Fig. 2.5. As each strategy was assumed to incur a cost of 100 units, the manageability weighted cost directly reflects the manageability score assigned to each strategy. The lowest points corresponding to the number of strategies are the optimal combinations keeping in view the factors of cost and manageability; however, these may not necessarily achieve the maximum improvement in the risk network expected loss.

As we assumed the decision maker as risk-neutral, the utility for risk network expected loss could be substituted for the expected utility for loss. Utility for manageability weighted mitigation cost was assumed as a decreasing linear function. Variation of both the normalised utility functions considering maximum values with the number of strategies is shown in Fig. 2.6. Normalised utility for the manageability weighted cost attains the maximum value once no strategy is selected and reduces to the minimum value in case of selecting all 6 strategies and vice versa

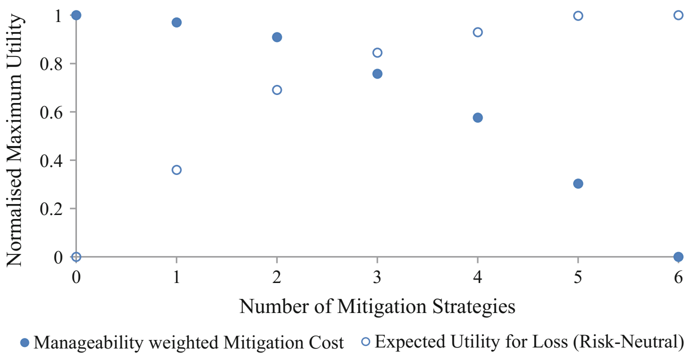

Fig. 2.6 Variation of utility values with respect to the number of strategies

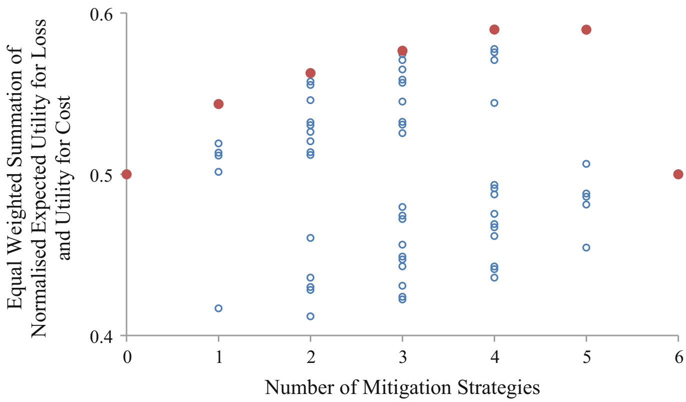

Fig. 2.7 Variation of equal weighted summation of normalised utility values with respect to the number of strategies

in case of normalised expected utility for loss. The two points corresponding to each number of strategies represent optimal combinations of strategies with respect to the two utility functions that might comprise different strategies. It is also important to realise the non-linear trend of utility functions.

Considering equal weights assigned to the two normalised utility functions, we analysed the behavior of the resulting function as shown in Fig. 2.7. It can clearly be observed that a risk-neutral decision maker will prefer implementing 4 strategies. Implementing all 6 strategies yields the minimum utility to the decision maker. Points appearing in red colour are the optimal combinations of strategies corresponding to the specific number of strategies.

We also conducted the sensitivity analysis through varying the weightings for normalised utility functions as shown in Fig. 2.8. Optimal strategies considering critical factors of cost, effectiveness, manageability and importance weighting of each normalised utility function are given in Table 2.8. The optimal strategies vary

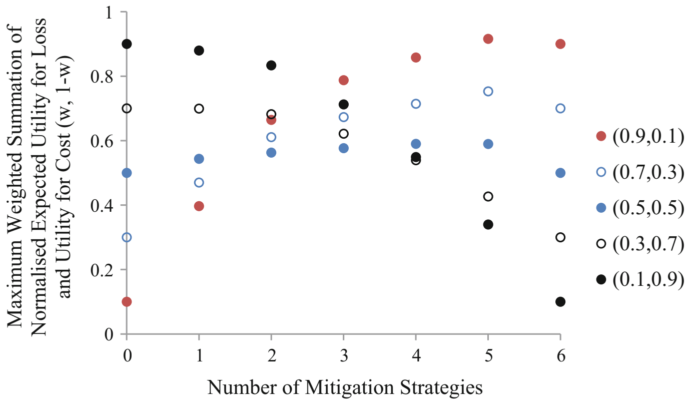

Fig. 2.8 Variation of maximum weighted summation of normalised utility values with respect to different weighting schemes and number of strategies

Table 2.8 Cost-effectiveness and manageability based prioritisation of strategies

Number of risk mitigation strategies	Prioritised strategies based on different weighting schemes [risk network expected loss (w), manageability weighted cost $(1 - w)$]				
	(0.9, 0.1)	(0.7, 0.3)	(0.5, 0.5)	(0.3, 0.7)	(0.1, 0.9)
1	6	6	6	2	2
2	1 and 6	1 and 6	2 and 6	2 and 3	2 and 3
3	1, 5 and 6	1, 5 and 6	1, 2 and 6	2, 3 and 5	2, 3 and 5
4	1, 3, 5 and 6	1, 3, 5 and 6	1, 2, 3 and 6	2, 3, 5 and 6	2, 3, 4 and 5
5	All except 4	All except 4	All except 4	All except 4	All except 1

in relation to different weighting schemes. Strategy 4 appears to be the least important strategy in all weighting schemes except the one in which minimum importance is given to normalised expected utility for loss ($w = 0.1$). For the weighting schemes considering relative importance of normalised expected utility for loss as $w = 0.9, 0.7, 0.5$, it is always optimal to implement the same combination of 5 strategies. The sensitivity analysis also helped in verifying the validity of our simulation model. Weighting schemes assigning substantial importance to the normalised utility for manageability weighted cost ($w = 01, 0.3$) result in implementing no strategy.

Evaluation of risk mitigation strategies through the proposed approach results in prioritisation of strategies considering holistic interaction of supply chain risks and strategies, and integrating important factors of cost, effectiveness and manageability of strategies within the modelling framework. As the approach is grounded in the theoretical framework of BBNs the resulting solution can be considered as viable.

However, it is assumed that all stakeholders would be willing to share their information and furthermore, elicited values would truly reflect the real-time risk scenario. Furthermore, modelling the risk attitude of a decision maker and assigning the relative importance weights to each utility function are challenging tasks.

2.4.2 Managerial Implications

The proposed modelling approach can help supply chain managers prioritise risk mitigation strategies taking into account the cost, effectiveness and manageability of strategies. Based on the risk attitude of a decision maker, optimal strategies can easily be prioritised. The approach is equally beneficial for managers dealing with complex supply chains as the development of a risk network does not necessarily follow the process flow of a supply chain. Causal mapping (qualitative modelling of BBNs) is beneficial to managers in identifying important risks and understanding dynamics between these risks.

2.5 Conclusions

SCRM is an active area of research focusing on effective management of risks ranging across the entire supply network. A number of models have been proposed to identify and assess risks. Similarly, researchers have also proposed appropriate strategies to mitigate specific risks. Limited studies have considered evaluating supply chain risk mitigation strategies within an interdependent setting of interacting supply chain risks and strategies. However, the evaluation of such strategies within a probabilistic network model capturing cost, effectiveness and manageability of potential strategies has not been addressed in the literature. Besides considering cost of implementing a strategy, it is also important to model the associated manageability-ease of implementing and managing a strategy.

In this chapter, we have proposed a modelling process of prioritising risk mitigation strategies on the basis of relative cost, effectiveness and manageability within a theoretically grounded framework of BBNs and demonstrated its application through a simulation study. Although we have assumed the decision maker as risk-neutral in the study, the proposed modelling process can be adapted to capture specific risk appetite of a decision maker which is represented by the unique utility function for loss and the relative importance of cost for implementing strategies.

In models ignoring manageability of strategies, it is assumed that all strategies are equally manageable. However, strategies differ in terms of manageability and such an assumption undermines the efficacy of models in evaluating strategies. The proposed process helps in determining optimal strategies for a given number of potential strategies. As the optimal strategies are different for cost-effectiveness and cost-effectiveness cum manageability based prioritisation schemes, we consider it important to model the manageability of strategies without which a decision maker would select and implement sub-optimal strategies.

We have represented risks and mitigation strategies by binary states. In future, risks can be modelled as continuous variables whereas strategies can be represented by a continuum of control levels. The proposed method is a first step towards modelling manageability of strategies within a framework of interdependent risks and strategies. It is important to consider the practical implications of adopting such an approach within a real case study. Another interesting and related theme is to model the adaptability of strategies and to explore the control levels of existing strategies yielding maximum net improvement in the expected loss less cost. Furthermore, less labour intensive elicitation methods may be developed and evaluated to help practitioners implement the process.

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