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## Conference Paper

# Selection of Optimal Redundancy Strategies for a Supply Network

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*Suggested Citation:* Qazi, Abroon; Quigley, John; Dickson, Alex; Gaudenzi, Barbara; Önsel, Şule (2015) : Selection of Optimal Redundancy Strategies for a Supply Network, In: Kersten, Wolfgang Blecker, Thorsten Ringle, Christian M. 978-3-7375-4059-9 (Ed.): Innovations and Strategies for Logistics and Supply Chains: Technologies, Business Models and Risk Management. Proceedings of the Hamburg International Conference of Logistics (HICL), Vol. 20, epubli GmbH, Berlin, pp. 419-450

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**Abroon Qazi, John Quigley, Alex Dickson, Barbara Gaudenzi and Şule Önsel**



# **Selection of Optimal Redundancy Strategies for a Supply Network**



# Selection of Optimal Redundancy Strategies for a Supply Network

*Abroon Qazi, John Quigley, Alex Dickson, Barbara Gaudenzi and Şule Önsel*

Supply chains have become more vulnerable because of increased globalization and interdependency between network actors and risks. It is, therefore, extremely important to model interdependency between risks taking into account the supply network configuration. In this paper, we have followed the existing concept of modelling supply network as a Bayesian belief network capturing network configuration, probabilistic interdependency between risks and losses resulting from the realization of risks. We propose a new method for evaluating efficacy of different combinations of redundancy strategies. For each node of the network, we incorporated a strategy of adding redundant resource as a risk management approach that would disengage the particular node from its parent node(s). The model was solved against the bi-criteria objective of maximizing normalized expected utility for loss exposure and normalized utility for cost of redundancy strategies keeping into account different risk attitudes and criteria weights. The model also helped in identifying optimal combination of strategies for specific allocation of budget as there could be different combinations of allocating redundant resources across the network resulting in sub-optimal values of risk measures.

**Keywords:** Supply Network Configuration, Bayesian Belief Network, Redundancy Strategies, Risk Attitudes

## 1. Introduction

Supply chain risk is characterized by both the probability of an event and its severity given that an event occurs (Handfield et al., 2011). According to Jüttner et al. (2003), "Supply chain risk management (SCRM) aims to identify the potential sources of supply chain risk and implement appropriate actions to avoid or contain supply chain vulnerability". Vulnerability is defined as an exposure to serious disturbances from risks within the SC as well as risks external to the SC (Christopher and Peck, 2004). 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 (Khan and Burnes, 2007).

Because of the complexity of global supply chains, there is need of developing robust risk management techniques for capturing interdependent risks ranging across the entire network (Khan and Burnes, 2007, Ghadge et al., 2012, Olson and Wu, 2010, Rao and Goldsby, 2009, Vanany et al., 2009). 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 (Gaudenzi and Borghesi, 2006). Similarly, the risk attitude of the stakeholder will influence the extent to which a specific control strategy needs to be implemented for mitigating controllable risks.

Bayesian belief network (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 (Sigurdsson et al.,

2001). BBNs have the potential of capturing interdependency between supply chain risks (Garvey et al., 2015, Badurdeen et al., 2014). However, current studies have not covered all stages of supply chain risk management process through BBNs.

## 1.1 Research Problem and Contribution

In this paper, we present a new modelling approach of capturing interdependency between risks using BBNs. The model incorporates supply network configuration, probabilistic interdependency between risks, resulting losses, redundancy strategies and associated costs. Implementation of a redundancy strategy through disconnecting a node from its parent nodes is a unique idea for evaluating the benefits associated with different combinations of such strategies across the network. Furthermore, we also consider risk attitude of the decision maker in choosing the optimal combination of redundancy strategies. We demonstrate our modelling approach through a simple example.

## 1.2 Paper Outline

Review of the literature is briefly presented in Section 2 including discussion on the studies focusing on Bayesian network based modelling of Supply chain risks and their limitations. The proposed modelling approach, risk measures and mathematical representation of the problem are elaborated in Section 3. Simulation study is illustrated in Section 4 followed by the presentation of results and discussion in Section 5. Finally, conclusion and future research agenda are described in Section 6.

## 2 Literature Review

Dickson (1989) defines risk management as “the identification, analysis and control of those risks which can threaten the assets or earning capacity of an enterprise.” Risk management is a continuous process which takes into account the past history of an organization in order to develop robust strategy for dealing with the present and future risk events. The actual process of risk management starts with assessment of two factors including likelihood of occurrence of a specific event and the resulting consequence (Cox and Townsend, 1998).

The Royal Society (1992) defines risk management as a process of making and implementing decisions pertaining to risks on the basis of risk estimation and evaluation in order to mitigate the impact of risk events through reduction of their likelihood and/or the impact of resulting consequence. Risk management does not need to be a highly sophisticated process rather it must be based on common sense and rationality (Smallman, 1996). According to White (1995), risk management process generally comprises following three stages:

1. Risk Identification. The first stage involves identification of hazards, potential failures and adverse consequences.
2. Risk Estimation. In the second stage of risk management process, probabilities of risk events are estimated and quantification of risks is performed.
3. Risk Evaluation. Risk evaluation involves estimating significance of risks, judging acceptability of risks and comparing risks against benefits.

According to Simon et al. (1997), all techniques related to the risk management process can be classified into following three groups:

1. Qualitative techniques. These are the techniques that seek to identify, describe, analyze and understand risks.
2. Quantitative techniques. These techniques incorporate modeling of risks for quantification.
3. Control techniques. These methods develop mitigating techniques in order to minimize the effect of risk events.

Manuj and Mentzer (2008) conducted an extensive literature review and a qualitative study comprising interviews and focus group meeting in order to develop a grounded theory for understanding global supply chain risks. According to them, "Global SCRM is the identification and evaluation of risks and consequent losses in the global supply chain, and implementation of appropriate strategies through a coordinated approach among supply chain members with the objective of reducing one or more of the following – losses, probability, speed of event, speed of losses, the time for detection of the events, frequency, or exposure – for supply chain outcomes that in turn lead to close matching of actual cost savings and profitability with those desired". It is important to consider that risk management is a continuous process and therefore, there is always a need for anticipating unforeseen risks and adapting the contingency plans.

According to Sodhi and Tang (2012), risks can be viewed with respect to three broad perspectives:

1. A 'butterfly' depiction of risk that separates underlying causes, actual events and ultimate consequences
2. Impact based perception in terms of disruptions and delays
3. Network perspective in terms of local-and-global causes and local-and-global effects

Sodhi et al. (2012) conducted a thorough study by carrying out direct observations of the researchers' output, gathering evidence through surveys of focus groups of researchers and seeking confirmation through a formal survey of a large group of researchers. They have identified following major gaps in the field of SCRM:

1. There is no clear consensus on the definition of SCRM
2. There is lack of research on the reactive strategies once the risk event has occurred
3. There is shortage of empirical research in the field

## **2.1 BBN based Models in SCRM**

BBNs have started gaining the interest of researchers in modelling supply chain risks (Badurdeen et al., 2014). BBNs offer a unique feature of modelling uncertainty combining both the statistical data and subjective judgment in case of non-availability of data (Sigurdsson et al., 2001, Kelangath et al., 2011, Qazi et al., 2014). Lockamy (2011, 2014) and Lockamy and McCormack (2009, 2012) developed a model for benchmarking supplier risks involving risk events related to supplier network, internal operations and external factors and found BBNs to be a very useful tool in assessing



risk exposure of a company to its suppliers. Dogan and Aydin (2011) developed a supplier selection method combining BBNs and Total Cost of Ownership method and advocated the efficacy of BBNs in dealing with incomplete or uncertain information of buyers about their suppliers.

Dogan (2012) introduced a model for selection of an international manufacturing site using BBNs. The proposed method allows exploring judgment of managers by following a systematic approach while globally considering all the relations among factors and between factors and objectives. Bardurdeen et al. (2014) developed supply chain risk taxonomy and a risk network map that captures interdependencies between risks. The model presents an effective tool to capture the interaction of risk factors and helps identifying key suppliers.

## 2.2 Limitations of the Existing BBN based Models

Many studies have focused on specific domain of SCRM like supplier selection, supplier evaluation and ranking. BBNs have not been fully explored for capturing the holistic view of supply network. Furthermore, it is not only important to consider the probabilistic interaction between risks but also take into account the resulting losses and costs and benefits associated with different control strategies. A comprehensive risk management modelling approach must be able to address all stages of risk management. Our study is supposed to bridge the mentioned research gap.

In a recent study conducted by Garvey et al. (2015), supply chain process and risks corresponding to various segments of the supply network are combined together and modelled as a BBN. New risk measures are also

proposed for identification of important elements within the supply network. The proposed model considers risk analysis under a given configuration whereas it is important to evaluate different risk mitigation strategies. Expected location risk contribution factor (ELRCF) is proposed as a measure for calculating the expected aggregated loss value including losses at the location and propagation of resulting losses across pure descendants corresponding to all possible scenarios at the specific location. Association of this measure with each element of the supply network rather than risk factor itself results in a major problem because for all different combinations of instantiation of risk factors corresponding to each element, propagation across the pure descendants only depends on the state of specific parent node that connects risks of that element to the rest of risk factors. Furthermore, in case of a large network, it will not be feasible to track the losses across pure descendants only. Instead of defining the measure for each element of supply network, it would be better to associate this measure with each risk factor. In that case, there would be no requirement of tracking various scenarios that increase exponentially with the increase in number of risk factors defined for each element of the supply network. Instead of relying on the pure descendants, entire Bayesian network can be easily monitored for change in the risk exposure.

Propagation ratio has been introduced as the total amount of propagation loss for all scenarios at a location divided by the total amount of loss for all scenarios. The main problem with this measure relates to the fact that it has not been normalized against a common denominator and therefore, it is not possible to compare different nodes on the basis of propagation ratio. A node having a propagation loss of 2 units against the total location

specific loss of 1 unit will result in the propagation ratio of 2 whereas another node having a propagation loss of 1500 units against the total location specific loss of 1000 units will yield the ratio of 1.5.

### 3 Proposed Model

A discrete supply chain risk diagram  $N = (X, G, P, L)$  is a four-tuple consisting of a directed acyclic graph (DAG),  $G = (V, E)$ , with nodes,  $V$ , representing discrete risk events,  $X_R$ , discrete redundancy strategies,  $X_S$ , and loss functions,  $L$ , and directed links,  $E$ , encoding dependence relations, a set of conditional probability distributions,  $P$ , containing a distribution,  $P(X_R|X_{pa(R)})$ , for each risk event,  $X_R$ , 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. Network expected loss,  $EL(X)$ , is calculated as follows:

$$EL(X) = \prod_{X_v \in X_R} P(X_v|X_{pa(v)}) \sum_{w \in V_L} l(X_{pa(w)}) \tag{1}$$

Supply network is considered to be in its standard configuration (SC) when all the redundancy strategies selected in the Bayesian network reflect real-time profile of these strategies in the supply network whereas supply network is considered to be in its contingency configuration (CC) when all the redundancy strategies in the Bayesian network are selected against the multi-criteria decision making of maximizing weighted summation of expected utility for loss exposure and utility of redundancy cost.

### 3.1 Risk Measures

We introduce two risk measures in order to evaluate the importance of risk factors in terms of their contribution towards the loss propagation across entire network.

#### 3.1.1 Loss Propagation Containment Measure (LPCM)

Loss propagation containment measure is the ratio between relative improvement in the network expected loss corresponding to complete mitigation of the risk factor and network expected loss for the standard configuration.

$$LPCM_{X_{R_i}} = \frac{EL(X) - EL(X|X_{R_i} = false)}{EL(X)_{SC}} \quad (2)$$

$$Average LPCM (\overline{LPCM}) = 1/n \sum_1^n LPCM_{X_{R_i}} \quad (3)$$

#### 3.1.2 Loss Propagation Spread Measure (LPSM)

Loss propagation spread measure is the ratio between range of network expected loss corresponding to the two extreme states of the risk factor and network expected loss for the standard configuration.

$$ELPSM_{X_{R_i}} = \frac{EL(X|X_{R_i} = true) - EL(X|X_{R_i} = false)}{EL(X)_{SC}} \quad (4)$$

$$Average LPSM (\overline{LPSM}) = 1/n \sum_1^n LPSM_{X_{R_i}} \quad (5)$$

### 3.2 Problem Statement

Given different levels of redundancy strategies and associated costs available at different nodes of the supply network, what is the optimal combination of these redundancy strategies yielding maximum utility for the decision maker?

#### 3.2.1 Objective Function

The objective function is to maximize the weighted sum of normalized expected utility for network loss and normalized utility for cost of redundancy strategies.

$$\max_{\gamma_{x_s} \in \gamma_{X_s}} w * \overline{EU}(X_{\gamma_{x_s}}) + (1 - w) * \overline{U}(C_{\gamma_{x_s}}) \tag{6}$$

$$EU(X) = \prod_{X_v \in X_R} P(X_v | X_{pa(v)}) \sum_{w \in V_U} u(X_{pa(w)}) \tag{7}$$

where  $\gamma_{X_s}$  is a set of all possible orderings of different states of n redundancy strategies  $(x_{s_1} \times x_{s_2} \times \dots \times x_{s_n})$

w is the relative importance of utility for loss exposure

$\overline{EU}(X)$  is normalized expected utility of the decision maker for loss

$C_{\gamma_{x_s}}$  is cost of implementing  $\gamma_{X_s}$  combination of redundancy strategies

$\overline{U}(C)$  is normalized utility of cost related to implementing redundancy strategies

## 4 An Illustrative Example

In order to demonstrate the application of our modelling approach, we make use of the supply network model presented by Garvey et al. (2015). However, our model is not the same as we aim to consider the evaluation of different redundancy strategies. The hypothetical supply network comprises raw material source (RM), two manufacturers (M1, M2), warehouse (W) and retailer (R). Each of the mentioned locations is termed as a risk element. In addition, there is another risk element 'W-R' which is the transportation link between the warehouse and retailer. Each risk element consists of risk factor(s) that can affect the respective element. Risk factors have been described in Table 1 with corresponding risk number and the risk element. The supply network is modelled in GeNIe as shown in Figure 1. All risk factors are represented by oval shaped nodes. Diamond shaped nodes represent loss values resulting from the realization of risks whereas rectangular shaped nodes denote redundancy strategies having binary states of 'Yes' and 'No'. Assumed (conditional) probability and loss values for the model are shown in Table 2.

Table 1 Description of risk factors

Risk No	Risk Factor	Risk Element
R1	Contamination	Raw material source
R2	Delay in shipment	Raw material source
R3	Machine failure	Manufacturer No. 2
R4	Machine failure	Manufacturer No. 1
R5	Delay in shipment	Manufacturer No. 1
R6	Delay in shipment	Manufacturer No. 2
R7	Overburdened employee	Warehouse
R8	Damage to inventory	Warehouse
R9	Delay in shipment	Warehouse
R10	Truck accident	Warehouse-Retailer
R11	Inventory shortage	Retailer
R12	Flood	Warehouse

Table 2 (Conditional) probability and loss values

$$[P(\text{risk} = F|\text{parents}) = 1 - P(\text{risk} = T|\text{parents})]$$

Parents				P(risk parents)						
				R1	R2	R3	R4	R5	R6	
R1	R2	R3	R4	T	T	T	T	T	T	
				0.4						
T					0.8					
F					0.3					
						0.2				
							0.3			
		T		T				0.7		
		T		F				0.4		
		F		T				0.6		
		F		F				0.1		
	T								0.9	
	T	F							0.6	
	F	T							0.5	
	F	F							0.2	
Loss				600	500	200	340	100	220	

Parents						P(risk parents)						
						R7	R8	R9	R10	R11	R12	
R5	R6	R7	R8	R9	R10	R12	T	T	T	T	T	T
							0.4					
			T			T		0.8				
			T			F		0.3				
			F			T		0.6				
			F			F		0.2				
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		
				T	T						0.9	
				T	F						0.7	
				F	T						0.6	
				F	F						0.2	
Loss							40	500	940	340	30	200



Conditional probability values of each risk factor given the implementation of respective redundancy strategy are given as Equations (8) and (9). Assumed utility functions and the value of criterion weighting 'w' are shown in Table 3. It is assumed that there is no redundancy strategy selected at any node under standard configuration.

$$P(\text{risk} = T | \text{redundancy} = \text{Yes}) = 0.0001 \quad (8)$$

$$P(\text{risk} = F | \text{redundancy} = \text{No}) = 0.9999 \quad (9)$$

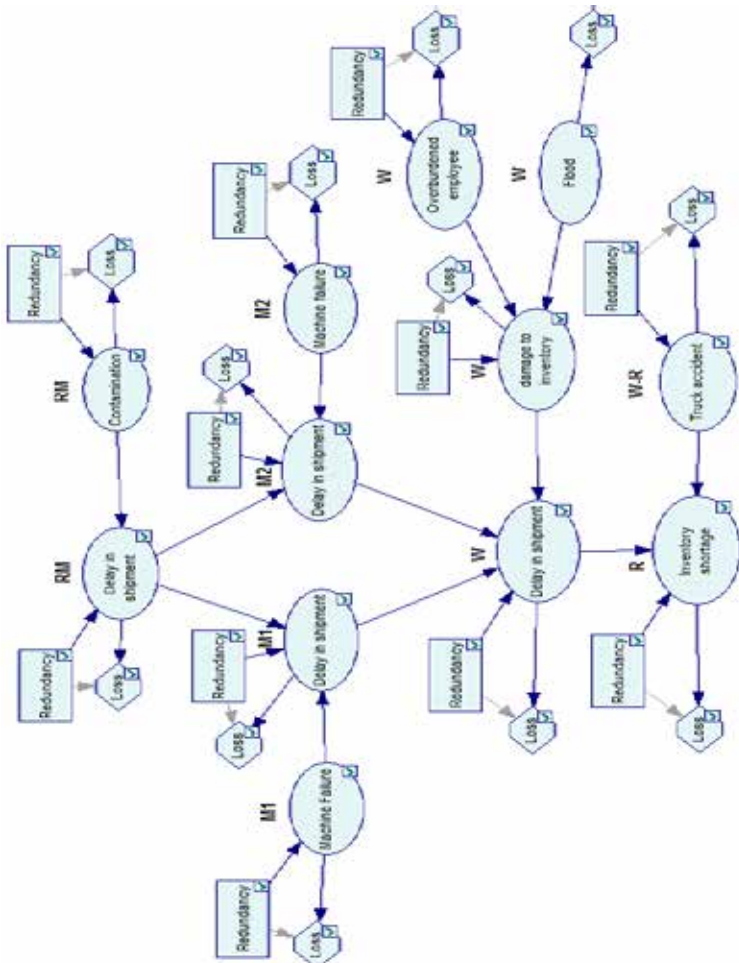


Figure 1 Supply network modelled as a Bayesian belief network in GeNIe

Table 3 Assumed parameters

Parameter	Assumption
$w$	0.5
$u(x)$ for risk neutral	$x$
$u(x)$ for risk taking	$x^2$
$u(x)$ for risk averse	$\sqrt{x}$
$U(C)$	$1 - cost/max\ cost$

## 5 Results and Discussion

Three models were developed in GeNIe according to the utility functions representing different risk attitudes of the decision maker as given in Table 3. For each model, results of GeNIe were exported to Microsoft Excel for evaluating the risk measures and utility values. Objective function given as Equation (6) was solved for the three types of decision makers. Optimal combination of redundancy strategies for the risk-neutral decision maker is shown in Table 4. Redundancy number corresponds to the respective risk factor number and implementation state of 'Yes' represents adding redundancy at that node. Optimal combination resulted in achieving weighted utility sum of 0.61 at the total redundancy cost of 880 units.

Table 4 Optimal combination of redundancy strategies (risk-neutral decision maker)

Redundancy No	Cost	Implement
1	350	Yes
2	300	No
3	100	No
4	200	No
5	50	Yes
6	140	Yes
7	30	No
8	200	Yes
9	500	No
10	140	Yes
11	20	No

Risk measures were evaluated for the optimal combination of redundancy strategies as shown in Figure 2. LPCM values of 0 for the risk factors R1, R5, R6, R8 and R10 relate to the fact that redundancy has been added at the mentioned nodes and therefore, the specific risk factors are disconnected from the influence of parent nodes. It is interesting to note that R9 is the

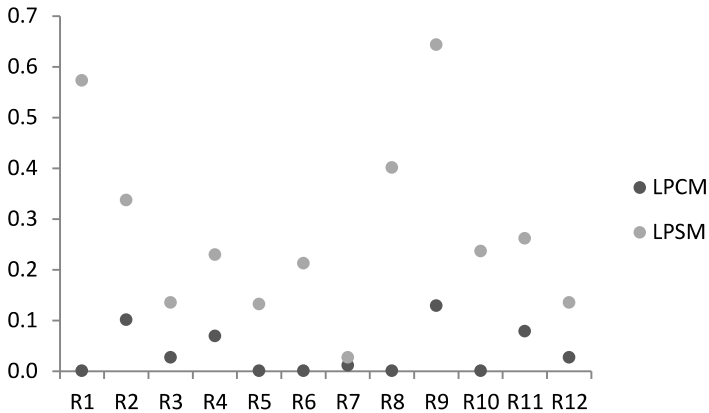


Figure 2 Risk measures of the supply network under contingency configuration (risk-neutral decision maker)

most important risk factor but the optimal combination of strategies does not necessitate implementation of redundancy strategy at the node.

Network expected loss is an important parameter that serves the central role in evaluation of our proposed risk measures. Network expected loss was evaluated for all combinations of redundancy strategies as shown in Figure 3. It can be observed that the rate of decrease in expected loss decreases gradually with the increase in redundancy cost. Furthermore, corresponding to each value of redundancy cost except the minimum and maximum costs, there are a number of possible combinations of strategies. All such combinations except the dark-shaded points result in inefficient solutions. Therefore, in case of a limited budget, the model can be used for selection of optimal mix of redundancy strategies for achieving the minimum value of network expected loss.

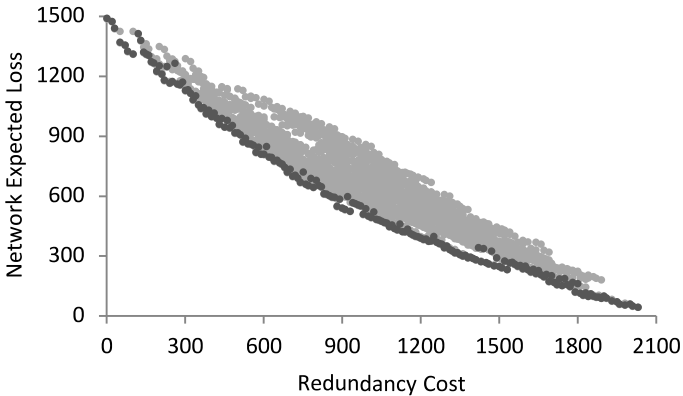


Figure 3 Variation of network expected loss with all possible combinations of redundancy strategies

Average LPCM represents the average value of LPCM for all the risk factors. Variation of this important measure is shown in Figure 4 with respect to all possible combinations of available redundancy strategies. As there are 11 redundancy strategies available across the supply network with each strategy having two states, there are a total of 2048 different combinations of redundancy strategies. The graph represents average LPCM values for all these 2048 strategies. Corresponding to a specific budget allocation for implementing redundancy strategies, there is a unique optimal combination of resource allocation across the network in order to achieve the minimum value of average LPCM. All such points are shown in dark shade representing the minimum points against specific redundancy cost. It is also evident from the graph that the rate of decrease declines sharply with the increase in redundancy cost.

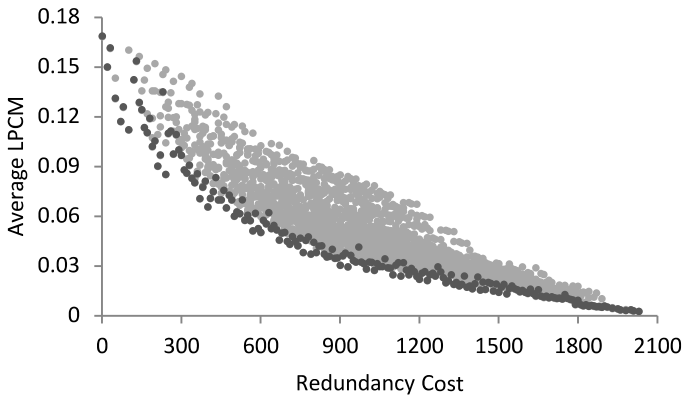


Figure 4 Variation of average LPCM with all possible combinations of redundancy strategies

Average LPSM represents the average value of LPSM for all the risk factors. Variation of this important measure is shown in Figure 5 with respect to all possible combinations of available redundancy strategies. Corresponding to a specific budget allocation for implementing a redundancy strategy, there is a unique optimal combination of resource allocation across the network in order to achieve the minimum value of average LPSM. All such points are shown in dark shade representing the minimum points against specific redundancy cost. It is also evident from the graph that the minimum average LPSM value remains unchanged after approximately 1300 units of redundancy cost.

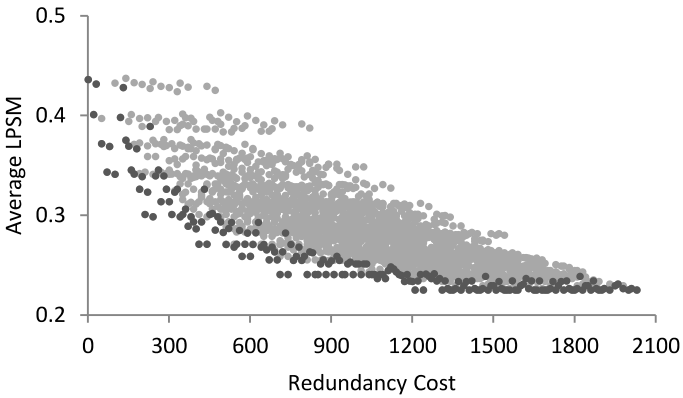


Figure 5 Variation of average LPSM with all possible combinations of redundancy strategies

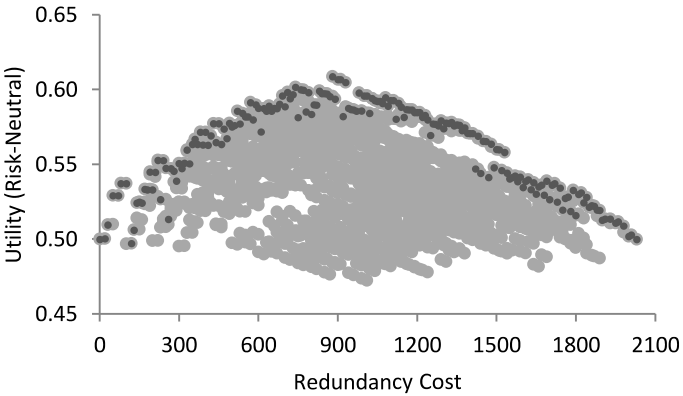


Figure 6 Variation of utility for risk-neutral decision maker with all possible combinations of redundancy strategies



Utility of the risk-neutral decision maker was calculated against all possible combinations of redundancy strategies as shown in Figure 6. There can be a number of combinations of redundancy strategies against specific budget allocation, however, only a unique combination results in maximizing the utility value. Dark shaded points represent all such combinations that maximize the utility values against specific redundancy cost. The maximum utility value is 0.61 corresponding to the total redundancy cost of 880 units. Utility of the risk-averse decision maker was calculated against all possible combinations of redundancy strategies as shown in Figure 7. Dark shaded points represent all combinations of redundancy strategies that maximize the utility values against specific redundancy cost. The maximum utility value is 0.62 corresponding to the mitigation cost of 930 units.

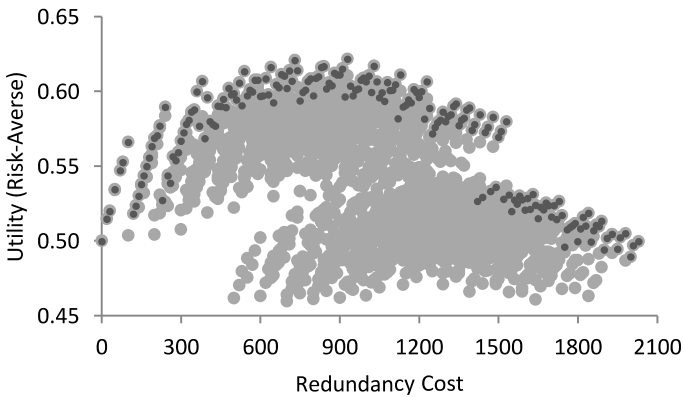


Figure 7 Variation of utility for risk-averse decision maker with all possible combinations of redundancy strategies

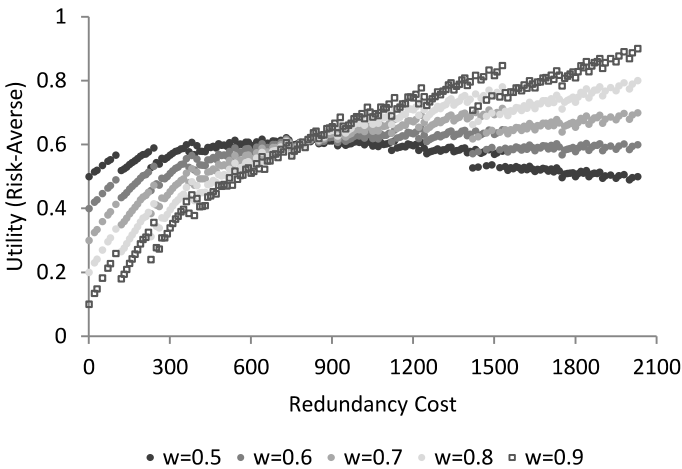


Figure 8 Variation of maximum utility for risk-averse decision maker with redundancy cost corresponding to different weighting schemes

It is important to consider that equal weightage was assigned to the two attributes of utility for cost and expected utility for loss exposure. Risk-averse decision makers might allocate higher weightage to the expected utility for loss and it might influence the results as shown in Figure 8. As more weightage is given to the expected utility for loss, the decision maker is less concerned with the disutility of redundancy cost and therefore, optimal solution is represented by a combination of strategies having higher redundancy cost. Utility of the risk-taking decision maker was calculated against all possible combinations of redundancy strategies as shown in Figure 9.

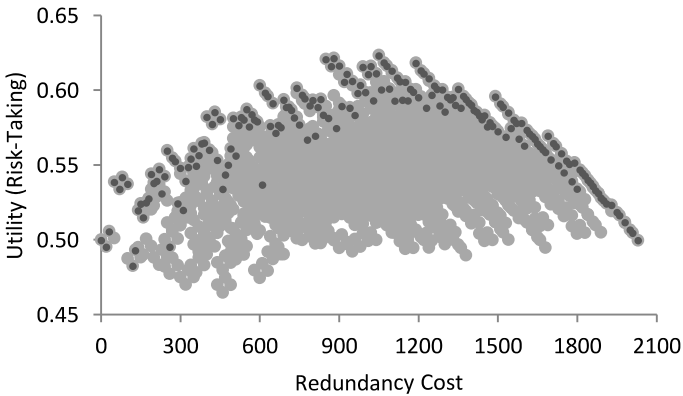


Figure 9 Variation of utility for risk-taking decision maker with all possible combinations of redundancy strategies

Dark shaded points represent all combinations of redundancy strategies that maximize the utility values against specific redundancy cost. The maximum utility value is 0.62 corresponding to the mitigation cost of 1050 units. Again, equal weightage was assigned to the two attributes of utility for cost and expected utility for loss exposure. Risk-averse decision makers might allocate lower weightage to the expected utility for loss and it might influence the results as shown in Figure 10. As lesser weightage is given to the expected utility for loss, the decision maker is more concerned with the disutility of redundancy cost and therefore, optimal solution is represented by a combination of strategies having lower redundancy cost.

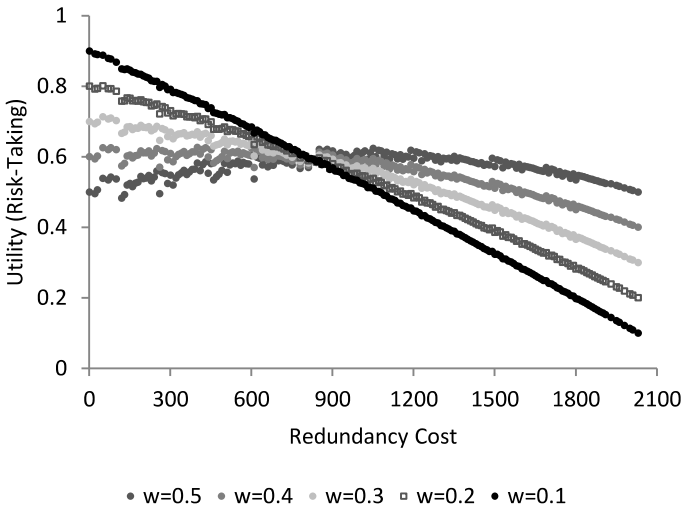


Figure 10 Variation of maximum utility for risk-taking decision maker with redundancy cost corresponding to different weighting schemes

Maximum utility values for all three risk attitudes of the decision maker were plotted against redundancy cost as shown in Figure 11. Equal weightage was assigned to both the criteria of the objective function. Initially, as the network expected loss decreased sharply with the increase in redundancy cost, risk-averse decision maker was more sensitive to this change in comparison with other types of decision maker. Afterwards, risk-taking decision maker was achieving higher utility values because of the reversal of the mentioned phenomenon.

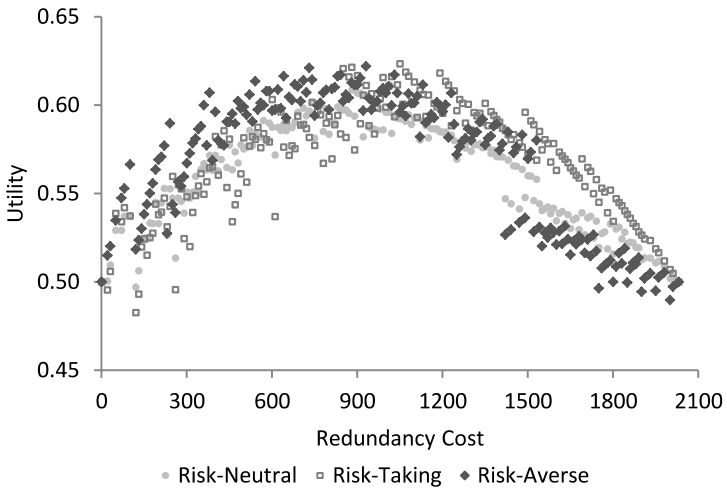


Figure 11 Variation of maximum utility values with redundancy cost for three different risk attitudes

It is also important to consider the variation of maximum expected utility values for loss and utility for cost with redundancy cost corresponding to three different risk attitudes as shown in Figure 12. Utility function of cost was assumed as linear. For risk-neutral decision maker, the graph of expected utility for loss is the mirror reflection of graph for expected loss.

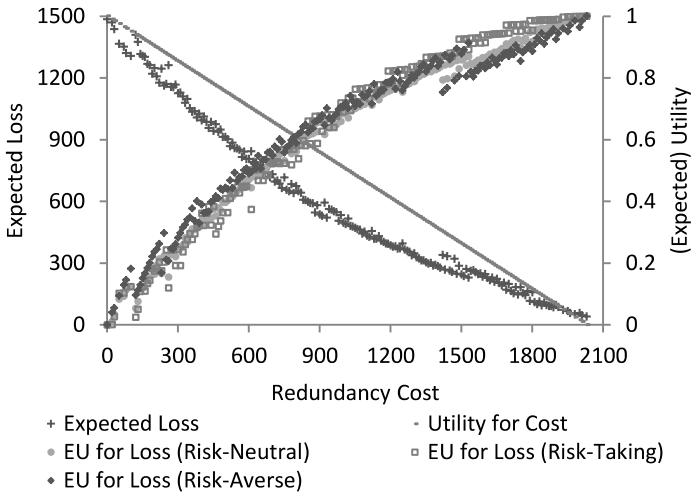


Figure 12 Variation of maximum expected utility values for loss and utility for cost corresponding to three different risk attitudes with redundancy cost

## 6 Conclusion

Supply chain risk management is an active area of research demanding development of effective techniques for capturing the interdependency between risks. Bayesian networks can be used for modelling the complex nature of interacting risks; however, current studies have not fully utilized the strength of this modelling technique. We have proposed a new approach of modelling the supply network configuration, probabilistic interdependency between risks, resulting losses and redundancy strategies that not

only captures the dynamics across supply chain risks but also covers all aspects of risk management process. New risk measures have been introduced for evaluating the relative contribution of each risk factor towards the network expected loss. The proposed method was demonstrated through a simple example taking into account the risk attitude of a decision maker. Redundancy strategy at a node was incorporated through disconnecting the node from its parent node(s). Therefore, in case of a redundancy strategy at a node, the probability of risk occurring at the node would be extremely low. Furthermore, given a certain budget allocation, it was shown that there would be a number of ineffective allocations of redundancy strategies across the network and the optimal combination could only be selected through the proposed method.

Risk attitude of the decision maker can highly influence the final outcome and therefore, it is important to consider the relative importance of expected utility for loss exposure with respect to the utility for redundancy cost. The proposed method is considered as an important contribution to the literature in terms of introducing a new approach of capturing the interdependency between risks and covering all stages of risk management process. In future, research may focus on the application of proposed method in different industries.

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