Detectability Based Prioritization of Interdependent Supply Chain Risks

Abroon Qazi[1(✉)], John Quigley[1], Alex Dickson[1], Şule Önsel Ekici[2], and Barbara Gaudenzi[3]

[1] Strathclyde Business School, University of Strathclyde, Glasgow, UK
{abroon.qazi, j.quigley, alex.dickson}@strath.ac.uk
[2] Industrial Engineering Department, Dogus University, Istanbul, Turkey
sonsel@dogus.edu.tr
[3] Faculty of Business Economics, University of Verona, Verona, Italy
barbara.gaudenzi@univr.it

Abstract. Supply chain risks must be assessed in relation to the complex interdependent interaction between these risks. Generally, risk registers are used for assessing the importance of risks that treat risks in silo and fail to capture the systemic relationships. Limited studies have focused on assessing supply chain risks within the interdependent network setting. We adapt the detectability feature from the Failure Modes and Effects Analysis (FMEA) and integrate it within the theoretically grounded framework of Bayesian Belief Networks (BBNs) for prioritizing supply chain risks. Detectability represents the effectiveness of early warning system in detecting a risk before its complete realization. We introduce two new risk measures and a process for prioritizing risks within a probabilistic network of interacting risks. We demonstrate application of our method through a simple example and compare results of different ranking schemes treating risks as independent or interdependent factors. The results clearly reveal importance of considering interdependency between risks and incorporating detectability within the modelling framework.

Keywords: Supply chain risks · Risk registers · Systemic · Detectability · Failure modes and effects analysis · Bayesian belief networks

1 Introduction

Supply chains have become complex because of the globalization and outsourcing in manufacturing industries. Global sourcing and lean operations are the main drivers of supply chain disruptions [1]. In addition to the network configuration based complexity, non-linear interactions between complex chains of risks categorized as 'systemicity' of risks [2] make it a daunting task to understand and manage these dynamics. Supply chain risk management (SCRM) is an active area of research that deals with the overall management of risks ranging across the entire spectrum of the supply chain including external risk factors. Besides the increase in the frequency of disruptions, supply chains are more susceptible because of the increasing interdependency between supply chain actors and humungous impact of cascading events [3]. Risk assessment

S. Liu et al. (Eds.): ICDSST 2016, LNBIP 250, pp. 73–87, 2016.
DOI: 10.1007/978-3-319-32877-5_6

comprises three main stages of risk identification, risk analysis and risk evaluation [4]. Generally, risk registers are used in managing risks that treat risks as independent factors [2, 5]. Limited studies have focused on exploring causal interactions between supply chain risks [6, 7]. However, no attempt has been made to capture the detectability associated with each risk within an interdependent network setting of interacting risks. Detectability is an important parameter of Failure Modes and Effects Analysis (FMEA) that represents the effectiveness of an early warning system in detecting a risk before its complete activation [8]. In case of risks having comparable values of the probability and impact, due attention should be given to the risk with lower chance of detection as substantial loss would have resulted by the time it gets noticed. In this study, we focus on the risk analysis stage of risk assessment and propose a new method of prioritizing supply chain risks through integrating the loss and detectability values of risks within the theoretically grounded framework of Bayesian Belief Networks (BBNs) encompassing complex probabilistic interactions between risks.

FMEA is a systematic approach of identifying different modes of failure and evaluating associated risks during the development stage of a product or service. It is known to have been implemented in 1963 for projects at NASA and later, the Ford utilized the technique in 1977 [9]. There are major shortcomings of using Risk Priority Number (RPN) as a measure of prioritizing risks that represents the product of occurrence, severity and detectability associated with each risk [9, 10]. Furthermore, risks are treated as independent factors in FMEA. We adapt the notion of detectability from the FMEA in our modelling framework.

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 [11]. They offer a unique feature of modelling risks combining both the statistical data and subjective judgment in case of non-availability of data [12]. In the last years, BBNs have started gaining the interest of researchers in modelling supply chain risks [7].

1.1 Research Problem and Contribution

In this study, we aim to address the decision problem of prioritizing supply chain risks considering the losses and detectability of such risks within an interconnected probabilistic network setting of interacting risks. Our proposed method contributes to the literature of SCRM in terms of introducing detectability based prioritization of interdependent supply chain risks that has never been explored.

1.2 Outline

A brief overview of the research conducted in SCRM is presented in Sect. 2. The modelling approach of prioritizing supply chain risks is described in Sect. 3 and demonstrated through an illustrative example in Sect. 4. Results corresponding to different ranking schemes and managerial implications are also described in the same section. Finally, conclusions and future research directions are presented in Sect. 5.

2 Literature Review

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"* [13]. 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 [14].

Bradley [15] proposed a new risk measurement and prioritization method to account for the characteristics of rare risks contributing to supply chain disruptions. The notion of detection was also incorporated within the model. Segismundo and Miguel [16] introduced a new FMEA based method of managing technical risks to optimize the decision making process in new product development.

Nepal and Yadav [10] presented a methodology for supplier selection in a global sourcing environment and used the techniques of BBNs and FMEA to quantify the risks associated with multiple cost factors. They also introduced rule-based evaluation of risk levels corresponding to 125 different combinations of severity, occurrence and detectability based linguistic variables. Tuncel and Alpan [17] used a timed petri nets framework to model and analyse a supply chain which was subject to various risks. They used the FMEA to identify important risks having higher values of RPN. The major shortcoming of these studies is treating risks as independent factors and/or prioritizing risks on the basis of RPN and related ordinal scales of occurrence, severity and detectability. Furthermore, these studies have not captured the holistic impact of interdependent risks.

In a recent study conducted by Garvey et al. [6], 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. Their proposed modelling framework differs from the existing BBN based studies in SCRM [7, 18–22] in terms of exploring the propagation impact of risks across the descendant nodes. They also incorporate the loss values within their modelling framework in order to overcome the major limitation of earlier studies that focused exclusively on the probabilistic interdependency between risks without capturing the relative impact of each risk. Qazi et al. [23] introduced new risk measures for capturing the relative impact of each risk on the entire network of interacting risks and proposed methods for selecting optimal combinations of risk mitigation strategies [24] and redundancy strategies [25] keeping in view the risk appetite of the decision maker. However, to the best of authors' knowledge, no attempt has been made to model the detectability of risks within the network setting of systemic risks.

BBNs present a useful technique of capturing interaction between risk events and performance measures [7]. Another advantage of using BBNs for modelling supply chain risks is the ability of back propagation that helps in determining the probability of an event that may not be observed directly. They 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 [26]. Another important feature of using BBNs is to conduct what-if scenarios [27]. 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 computational challenges associated with the increase in number of nodes.

3 Proposed Modelling Approach

Based on the efficacy of BBNs in capturing interdependency between risks, we consider BBN based modeling of supply chain risks as an effective approach. Such a modeling technique can help managers visualize dynamics between supply chain risks and adopt holistic approach towards managing risks [12, 28]. BBNs have already been explored in the literature of SCRM, however, our proposed BBN based modelling approach is unique in terms of integrating the probabilistic interdependency between risks and loss and detectability associated with each risk within the network setting of interacting supply chain risks.

3.1 Assumptions

Our model is based on following assumptions:

1. Supply chain risks and corresponding risk sources are known and these can be modelled as an acyclic directed graph which is an important requirement of adopting the BBN based modelling approach.
2. All risks are represented by binary states. Instead of focusing on a continuous range of risk levels, we assume that either a risk happens or there is a normal flow of activities/processes (condition of no risk).
3. Conditional probability values for the risks and associated loss and detectability values can be elicited from the stakeholders and the resulting BBN represents close approximation to the actual perceived risks and their interdependency.

3.2 Supply Chain Risk Network

A discrete supply chain risk network $RN = (X_R, G, P, L, D)$ is a five-tuple comprising:

- a directed acyclic graph (DAG), $G = (V, E)$, with nodes, V, representing a set of discrete supply chain risks and risk sources, $X_R = \{X_{R_1}, \ldots, X_{R_n}\}$, loss functions, L, and detectability weighted loss functions, D 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, X_{R_i}
- a set of loss functions, L, containing one loss function, $l(X_{R_i})$, for each node X_{R_i}
- a set of detectability weighted loss functions, D, containing one detectability weighted loss function, $d(X_{R_i})$, for each node X_{R_i}.

The prior marginal of a supply chain risk or risk source, X_{R_i}, is given by:

$$\begin{aligned} P(X_{R_i}) &= \sum\nolimits_{Y \in X_R \setminus \{X_{R_i}\}} P(X_R) \\ &= \sum\nolimits_{Y \in X_R \setminus \{X_{R_i}\}} \prod\nolimits_{X_{R_i} \in X_R} P(X_{R_i}|X_{pa(R_i)}) \end{aligned} \tag{1}$$

Risk network expected loss, $RNEL(X)$, representing the expected loss across the entire network of interacting risks is an important parameter for assessing the risk level of the supply network under a given configuration of risk mitigation strategies at a specific time. $RNEL(X)$ is the summation of expected loss values across all the risk nodes as follows:

$$RNEL(X) = \sum\nolimits_{X_R} P(X_{R_i}) l(X_{R_i}) \tag{2}$$

Risk network expected detectability weighted impact, $RNEDI(X)$, integrates the detectability feature of each risk within the framework of assessing risk level of the supply network under a given configuration of risk mitigation strategies at a specific time. $RNEDI(X)$ is the summation of expected detectability weighted loss values across all the risk nodes as follows:

$$RNEDI(X) = \sum\nolimits_{X_R} P(X_{R_i}) d(X_{R_i}) \tag{3}$$

Risk Measures. We introduce two risk measures namely Risk network expected loss propagation measure ($RNELPM$) and Risk network expected detectability weighted impact measure ($RNEDIM$) in order to evaluate the relative contribution of each supply chain risk towards the propagation of loss across the entire network of risks. The major contribution of these risk measures is their merit of capturing the network-wide propagation of impact across the web of interconnected risks. The later risk measure is superior to the former in terms of assigning detectability value to each risk and modelling the efficacy of early warning system(s) in detecting risks.

$RNELPM$ is the relative contribution of each risk factor to the propagation of loss across the entire network of supply chain risks given the scenario that the specific risk has happened.

$$RNELPM_{X_{R_i}} = RNEL(X|X_{R_i} = true) * P(X_{R_i} = true) \tag{4}$$

RNEDIM is the relative contribution of each risk factor to the propagation of detectability weighted impact across the entire network of supply chain risks given the scenario that the specific risk has happened.

$$RNEDIM_{X_{R_i}} = RNEDI(X|X_{R_i} = true) * P(X_{R_i} = true) \tag{5}$$

Detectability Scale. Considering detectability as an important parameter in our modelling framework, we follow the detectability scale as shown in Table 1. A detectability value represents the manageability of each risk during the timeframe between reception of early warning signal and complete realization of the risk.

Table 1. Detectability scale [8]

Detectability value	Description
9 or 10	There is no detection method available or known that will provide an alert with enough time to plan for a contingency.
7 or 8	Detection method is unproven or unreliable; or effectiveness of detection method is unknown to detect in time.
5 or 6	Detection method has medium effectiveness.
3 or 4	Detection method has moderately high effectiveness.
1 or 2	Detection method is highly effective and it is almost certain that the risk will be detected with adequate time.

3.3 Modelling Process

Our proposed method comprises three main stages namely problem structuring, instantiation and inference.

Problem Structuring. Supply chain risks and risk sources are identified through involving all the stakeholders of the supply chain. The network structure is developed through connecting the arcs across related risk sources and risks and all nodes are expressed as statistical variables. The problem owner needs to ensure that the model is developed to represent the actual interdependency between risks. The model builder can assist in structuring the model keeping in view the mechanics of a BBN [29].

Instantiation. This stage involves evaluation of (conditional) probabilities either through elicitation from the experts or extraction from the data. Loss and detectability values are also elicited. Probability elicitation is the most difficult task of the modelling process as the experts find it challenging to describe the conditional probabilities.

Inference. In this stage, key risks are identified through measuring the *RNELPM* and *RNEDIM* for each risk and risk source. The beliefs can also be propagated easily once the information on any risk or combination of risks becomes available.

4 An Illustrative Example

4.1 Assumed Risk Network and Modelling Parameters

We demonstrate application of our proposed method through adapting a simple supply chain risk network [6] as shown in Fig. 1. The model was developed in GeNIe [30]. The supply network comprises a raw material source, two manufacturers, a warehouse and retailer. Risks and risk sources are represented by nodes (shown as bar charts) with values reflecting the updated marginal probabilities. Each risk is represented by binary states of True (T) and False (F). Assumed loss values and detectability scores are shown in Table 2 and (conditional) probability values of the risks are depicted in Table 3. These parameters specific to a real case study can be elicited from experts through conducting interviews and focus group sessions.

Table 2. Loss values and detectability scores for the supply chain risks

Supply chain element	Risk	Risk ID	Loss	Detectability
Raw material source (RM)	Contamination	R1	200	1
	Delay in shipment	R2	100	1
Manufacturer-I (M1)	Machine failure	R4	350	1
	Delay in shipment	R5	100	2
Manufacturer-II (M2)	Machine failure	R3	400	2
	Delay in shipment	R6	150	1
Warehouse (W)	Overburdened employee	R7	150	10
	Damage to inventory	R8	100	9
	Delay in shipment	R9	100	8
	Flood	R12	50	10
Warehouse to retailer (W-R)	Truck accident	R10	200	9
Retailer (R)	Inventory shortage	R11	50	2

4.2 Results and Analysis

Once the model was developed and populated with all the parameters, it was updated for obtaining the marginal probabilities of interdependent risks. We analyzed risks with respect to five ranking schemes in order to appreciate the underlying differences. The five schemes can be categorized into two main streams; conventional methods relying on risk registers and the FMEA based tools treating risks as independent factors and the ranking schemes based on our proposed risk measures considering the holistic interaction between interdependent risks. The updated marginal probabilities were used in assessing risks for all the five schemes. However, in case of methods assuming risks as independent factors, the probabilities are assigned to individual risks without modelling the risk network. Risk measures were calculated for each risk in order to prioritize risks against the three schemes relying on our proposed approach. Finally, we compared the results of all these schemes in order to understand the extent of variation.

Conventional Method of Prioritizing Supply Chain Risks (Scheme 1). As conventional methods rely on the assumption that risks are independent of each other, the resulting ranking profile does not capture interdependency between the risks. Considering

Table 3. (Conditional) probability values: $P(risk = F|parents) = 1 - P(risk = T|parents)$

Parents				$\boldsymbol{P(risk = True|parents)}$					
$R1$	$R2$	$R3$	$R4$	$R1$	$R2$	$R3$	$R4$	$R5$	$R6$
				0.3					
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	T							0.9
	T	F							0.6
	F	T							0.5
	F	F							0.2

Parents							$\boldsymbol{P(risk = True|parents)}$					
$R5$	$R6$	$R7$	$R8$	$R9$	$R10$	$R12$	$R7$	$R8$	$R9$	$R10$	$R11$	$R12$
							0.3					
		T				T		0.95				
		T				F		0.6				
		F				T		0.8				
		F				F		0.1				
T	T		T						0.9			
T	T		F						0.4			
T	F		T						0.8			
T	F		F						0.3			
F	T		T						0.8			
F	T		F						0.3			
F	F		T						0.7			
F	F		F						0.1			
										0.3		
				T	T						0.9	
				T	F						0.7	
				F	T						0.8	
				F	F						0.1	
												0.2

the two important factors of probability and impact associated with each risk, we prioritized the risks as shown in Fig. 2. The curve represents the risk level (product of probability and impact) of the most critical risk namely R4. However, the result would only be valid in case of all risks modelled as independent factors with no arc connected across any pair of risks. Similar ranking scheme is adopted in most of the ranking schemes based on risk registers.

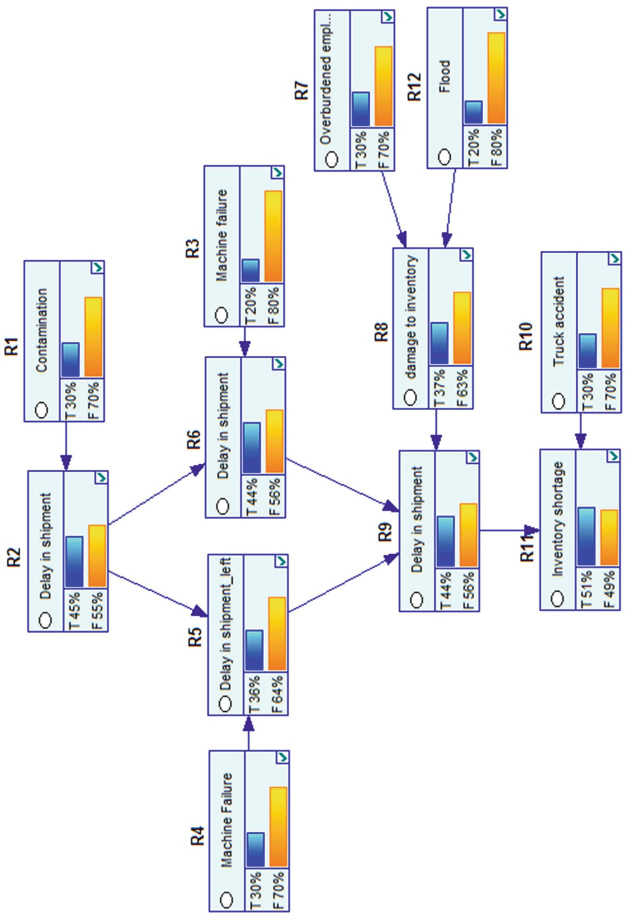

Fig. 1. Bayesian network based model of a supply network (adapted from Garvey et al. [6])

FMEA Based Prioritization of Supply Chain Risks (Scheme 2). In FMEA based ranking schemes, risks are prioritized with regard to the relevant product of occurrence, severity and detectability scores. We used a modified FMEA technique and analyzed risks on the basis of probability and impact values and detectability score as shown in Fig. 3. The curve contains the risk 'R10' with the highest value of modified RPN and serves as a reference level of risk for assessing other risks. In contrast with the results of ranking scheme based on conventional method, R4 is not considered as an important risk. This scheme also treats risks as independent factors and therefore, the resulting ranking profile is not valid for the network setting considered in our simulation study.

***RNELPM* Based Prioritization of Supply Chain Risks (Scheme 3).** This ranking scheme captured the interdependency between risks as depicted in Fig. 1. The relative importance of each risk is characterized by the associated value of *RNELPM* that can be assessed with reference to the curve containing the most critical risk as shown in

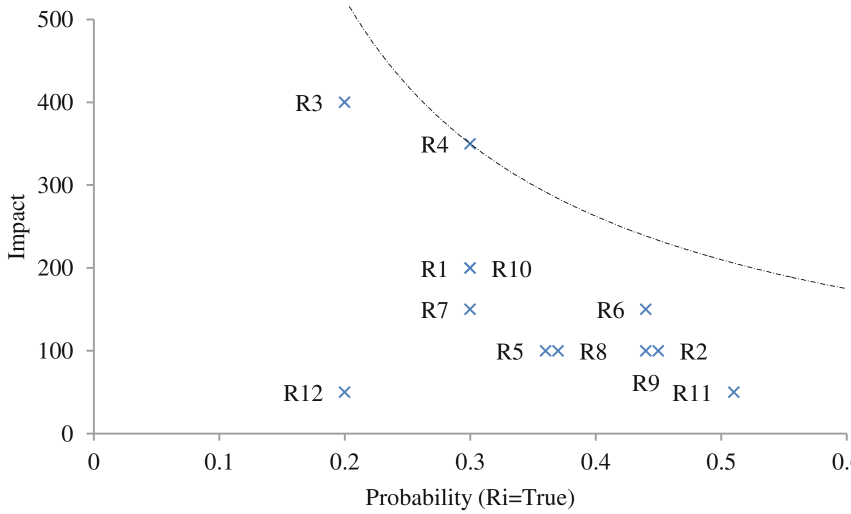

Fig. 2. Prioritization of supply chain risks based on conventional method

Fig. 4. As this scheme considers the attributes of probabilistic interdependency between risks, loss values and position of risks within an interconnected web of risks, the results reflect realistic nature of complex interactions between risks and risk sources. R11 appears to be the most significant risk taking into account its position in the network and strong relationship with connected nodes. However, this scheme assumes that all risks possess the same level of detectability. R3 and R12 are the least important risks because of combined effect of lower probability and loss values and weaker interdependency with the connected risks.

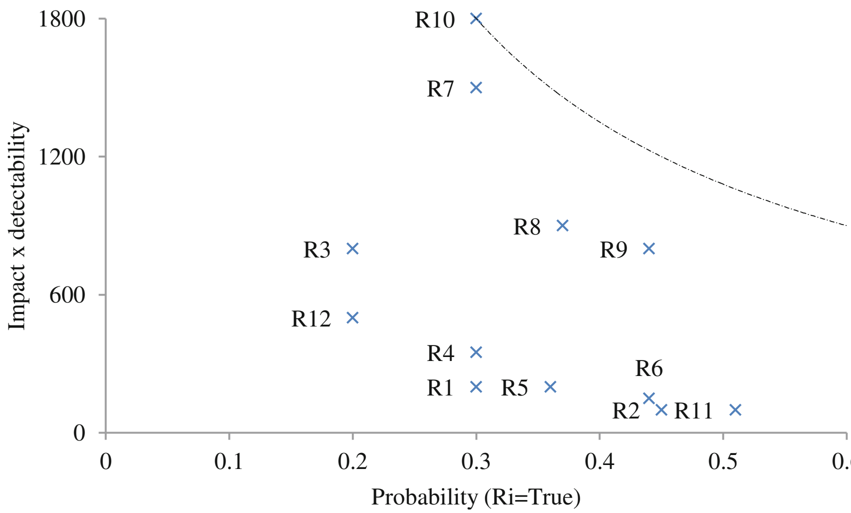

Fig. 3. Prioritization of supply chain risks based on modified FMEA

***RNEDIM* Based Prioritization of Supply Chain Risks (Scheme 4).** *RNEDIM* is an enhancement of the *RNELPM* as the *RNEDIM* based ranking scheme incorporates an important attribute of detectability in prioritizing risks. The risks are mapped on the basis of their detectability based propagation impact as shown in Fig. 5. Although the result of this scheme seems to be similar to that of the *RNELPM* based ranking scheme,

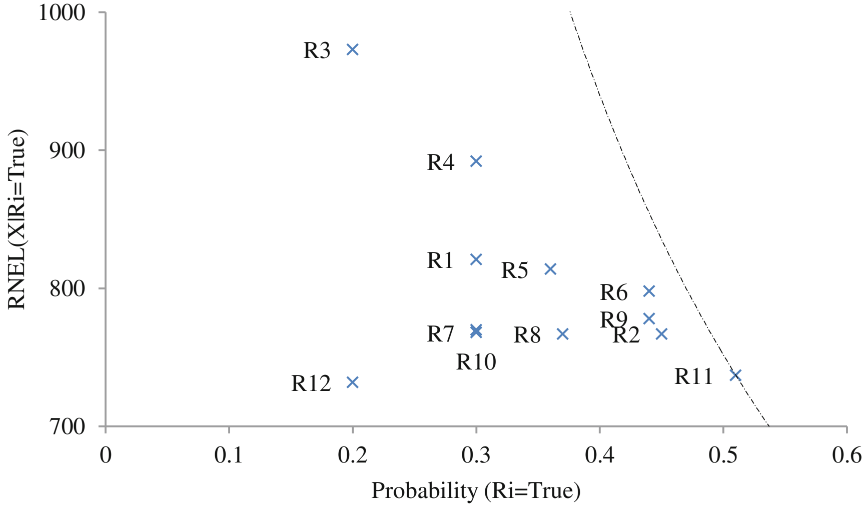

Fig. 4. *RNELPM* based prioritization of supply chain risks

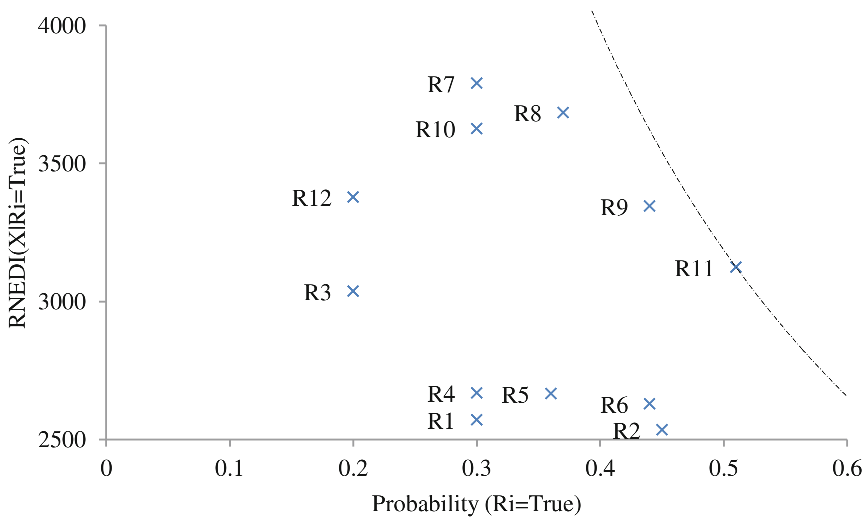

Fig. 5. *RNEDIM* based prioritization of supply chain risks

there are some obvious differences like in case of the ranking of R6, R7 and R8. Furthermore, it is important to understand that the unique array of loss and detectability values assumed in the study engendered such similar results.

***RNELPM* and *RNEDIM* Based Prioritization of Supply Chain Risks (Scheme 5).** As the *RNEDIM* does not directly reflect the perceived risk exposure, it is important to relate the two ranking schemes based on *RNEDIM* and *RNELPM*. We normalized the two risk measures for each risk and prioritized risks through calculating the modulus of each vector associated with specific risk in the two-dimensional plane as shown in Fig. 6. This combined ranking scheme takes into consideration the detectability and contribution of each risk towards the network-wide propagation of loss. R11 (R12) is the most (least) important risk.

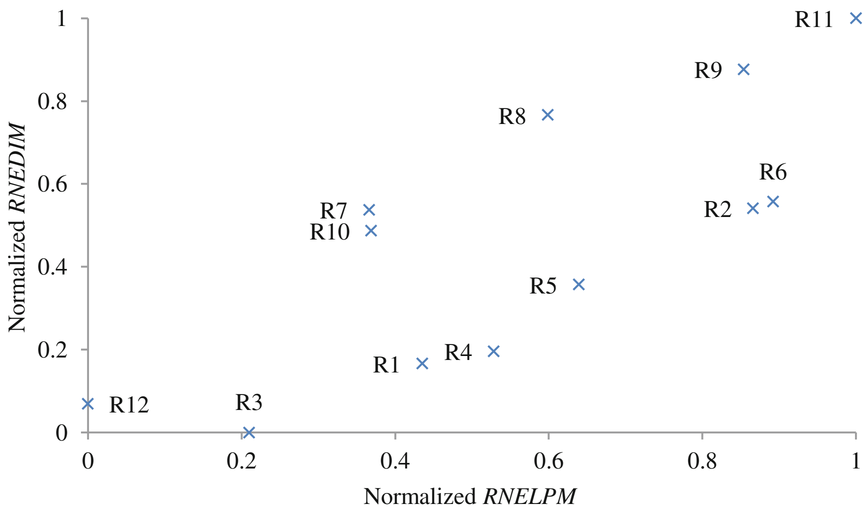

Fig. 6. *RNELPM* and *RNEDIM* based prioritization of supply chain risks

Comparison of Schemes for Prioritizing Supply Chain Risks. In order to realize the variability in results corresponding to the five ranking schemes, we compared the results as shown in Table 4. Generally, the results are similar for the last three schemes treating risks as interdependent factors whereas the results are quite different corresponding to the Schemes 1&2, 1&3 and 2&4 and therefore, it is important to capture interdependency between risks within the ranking framework. Furthermore, the variation in the detectability and/or loss values would yield quite different results even in case of interdependency based ranking schemes.

Table 4. Comparison of different prioritization schemes

Risk ID	Ranking of risks				
	Scheme 1	Scheme 2	Scheme 3	Scheme 4	Scheme 5
R1	4	10	8	10	10
R2	6	12	3	5	4
R3	2	5	11	12	11
R4	1	6	7	9	9
R5	10	8	5	8	6
R6	3	9	2	4	3
R7	6	2	10	6	7
R8	9	4	6	3	5
R9	8	3	4	2	2
R10	4	1	9	7	8
R11	11	11	1	1	1
R12	12	7	12	11	12

4.3 Managerial Implications

The proposed modelling approach can help supply chain managers prioritize supply chain risks taking into account the probabilistic interdependency between risks and loss and detectability associated with each risk. The approach is effective for assessing risks of complex supply chains as the risk network does not necessarily follow the process flow of the supply chain. The comparison of different ranking schemes can also help managers understand the limitations of each scheme and appreciate the importance of treating risks as interdependent factors. Causal mapping (qualitative modelling of BBNs) is beneficial to the managers in identifying important risks and understanding the dynamics between these risks.

5 Conclusion and Future Research

Limited studies have focused on capturing the interdependent interaction between risks within the literature of SCRM. Generally, risk registers are used for prioritizing risks that rely on the assumption of risks as independent factors. Detectability is an important concept in the FMEA that reflects the effectiveness of early warning system in detecting a risk before its complete realization. We adapted the concept of detectability from FMEA and integrated it within the theoretically grounded framework of BBNs comprising interconnected supply chain risks and associated loss values and demonstrated its application through an illustrative example. We also introduced two new risk measures for prioritizing supply chain risks and compared the results of our proposed ranking scheme with other schemes relying on independent or interdependent notion of risks. The results clearly revealed importance of considering detectability of risks in prioritizing supply chain risks as the risks having ineffective detection system must be given due consideration.

Our model is based on a number of assumptions. We have represented risks by binary states. In future, risks can be modelled as continuous variables and similarly, loss values can also be represented as continuous distributions. Our proposed method is a first step towards modelling detectability of risks within a framework of interdependent risks and risk sources. The proposed approach needs validation through conducting case studies.

References

1. Son, J.Y., Orchard, R.K.: Effectiveness of policies for mitigating supply disruptions. Int. J. Phys. Distrib. Logistics Manage. **43**(8), 684–706 (2013)
2. Ackermann, F., Howick, S., Quigley, J., Walls, L., et al.: Systemic risk elicitation: using causal maps to engage stakeholders and build a comprehensive view of risks. Eur. J. Oper. Res. **238**(1), 290–299 (2014)
3. Handfield, R., Blackhurst, J., Craighead, C.W., Elkins, D.: Introduction: a managerial framework for reducing the impact of disruptions to the supply chain (2011)
4. Standards, Risk Management: Principles and Guidelines (AS/NZS ISO 31000: 2009). Standards Australia, Sydney (2009)
5. Khan, O., Christopher, M., Burnes, B.: The impact of product design on supply chain risk: a case study. Int. J. Phys. Distrib. Logistics Manage. **38**(5), 412–432 (2008)
6. Garvey, M.D., Carnovale, S., Yeniyurt, S.: An analytical framework for supply network risk propagation: a Bayesian network approach. Eur. J. Oper. Res. **243**(2), 618–627 (2015)
7. Badurdeen, F., Shuaib, M., Wijekoon, K., Brown, A., et al.: Quantitative modeling and analysis of supply chain risks using Bayesian theory. J. Manuf. Technol. Manage. **25**(5), 631–654 (2014)
8. Carbone, T.A., Tippett, D.D.: Project risk management using the project risk FMEA. Eng. Manage. J. **16**(4), 28–35 (2004)
9. Gilchrist, W.: Modelling failure modes and effects analysis. Int. J. Qual. Reliab. Manage. **10** (5), 16–23 (1993)
10. Nepal, B., Yadav, O.P.: Bayesian belief network-based framework for sourcing risk analysis during supplier selection. Int. J. Prod. Res. **53**(20), 6114–6135 (2015)
11. Jensen, F.V., Nielsen, T.D.: Bayesian Networks and Decision Graphs. Springer, New York (2007)
12. Qazi, A., Quigley, J., Dickson, A.: A novel framework for quantification of supply chain risks. In: 4th Student Conference on Operational Research, University of Nottingham, UK (2014)
13. Christopher, M., Lee, H.: Mitigating supply chain risk through improved confidence. Int. J. Phys. Distrib. Logistics Manage. **34**(5), 388–396 (2004)
14. Sodhi, M.S., Tang, C.S.: Managing Supply Chain Risk. International Series in Operations Research and Mangement Science, vol. 172. Springer, New York (2012)
15. Bradley, J.R.: An improved method for managing catastrophic supply chain disruptions. Bus. Horiz. **57**(4), 483–495 (2014)
16. Segismundo, A., Miguel, P.A.C.: Failure mode and effects analysis (FMEA) in the context of risk management in new product development. Int. J. Qual. Reliab. Manage. **25**(9), 899–912 (2008)
17. Tuncel, G., Alpan, G.: Risk assessment and management for supply chain networks: a case study. Comput. Ind. **61**(3), 250–259 (2010)

18. Lockamy, A., McCormack, K.: Analysing risks in supply networks to facilitate outsourcing decisions. Int. J. Prod. Res. **48**(2), 593–611 (2009)
19. Lockamy, A.: Benchmarking supplier risks using Bayesian networks. Benchmarking: Int. J. **18**(3), 409–427 (2011)
20. Lockamy, A., McCormack, K.: Modeling supplier risks using Bayesian networks. Industr. Manage. Data Syst. **112**(2), 313–333 (2012)
21. Lockamy, A.: Assessing disaster risks in supply chains. Industr. Manage. Data Syst. **114**(5), 755–777 (2014)
22. Dogan, I., Aydin, N.: Combining Bayesian networks and total cost of ownership method for supplier selection analysis. Comput. Industr. Eng. **61**(4), 1072–1085 (2011)
23. Qazi, A., Quigley, J., Dickson, A., Gaudenzi, B.: A new modelling approach of evaluating preventive and reactive strategies for mitigating supply chain risks. In: Corman, F., Voß, S., Negenborn, R.R. (eds.) ICCL 2015. LNCS, vol. 9335, pp. 569–585. Springer, Heidelberg (2015). doi:10.1007/978-3-319-24264-4_39
24. Qazi, A., Quigley, J., Dickson, A., Gaudenzi, B., et al.: Evaluation of control strategies for managing supply chain risks using Bayesian belief networks. In: International Conference on Industrial Engineering and Systems Management (2015)
25. Qazi, A., Quigley, J., Dickson, A., Gaudenzi, B., et al.: Selection of optimal redundancy strategies for a supply network. In: Kirsten, W., Blecker, T., Ringle, C.M. (eds.) Hamburg International Conference of Logistics (2015)
26. Onisko, A.: Medical diagnosis. In: Pourret, O., Naïm, P., Marcot, B. (eds.) Bayesian Networks: A Practical Guide to Applications, vol. 73, pp. 15–32. Wiley, West Sussex (2008)
27. Blodgett, J.G., Anderson, R.D.: A Bayesian network model of the consumer complaint process. J. Serv. Res. **2**(4), 321–338 (2000)
28. Qazi, A., Quigley, J., Dickson, A.: Supply chain risk management: systematic literature review and a conceptual framework for capturing interdependencies between risks. In: 5th International Conference on Industrial Engineering and Operations Management, Dubai (2015)
29. Sigurdsson, J.H., Walls, L.A., Quigley, J.L.: Bayesian belief nets for managing expert judgement and modelling reliability. Qual. Reliab. Eng. Int. **17**(3), 181–190 (2001)
30. GeNIe. The Decision Systems Laboratory, GeNIe and SMILE (2015). http://genie.sis.pitt.edu/about.html. Accessed 5 June 2015