Modelling and Managing Systemic Risks in Supply Chains

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Abstract
A structured review of the supply chain and risk management literature supports an analysis of the sources and types of risks anticipated in supply chains and networks. We discuss alternative modelling approaches, such as Bayesian Belief Nets (BBN), System Dynamics, Fault and Event Trees, which are evaluated against the criteria characterizing systemic risks that emerge from the literature review. Finally, we briefly present an empirical pilot case study is conducted with a public sector organization in charge of a pharmaceutical distribution network to explore the feasibility of a BBN modelling approach.

Keywords: risk modelling, Bayesian belief networks, pharmaceutical distribution

Introduction
As noted by a growing number of authors (for instance, Jüttner, Peck & Christopher (2003), Trkman & McCormack, 2009), risk management is an important contributor to operations management in general, and supply chain management in particular. Increasingly complex supply chains and networks provide greater opportunities for risk events, especially rare events arising due to dependencies within the system that may have a low probability of occurrence but high consequence. However, the risk management processes commonly advocated in the academic literature are based on classification taxonomies that assume independent events. (The references given above are quite representative in that respect.) Such theoretical classifications provide a logical rationale for the risk registers used in practice. The limitations of risk registers and the naivety of not considering dependencies are acknowledged in related area such as project risk management and technical risk analysis (see, for instance, Williams, 2002). In these domains the importance of systemic risk is established. Therefore the purpose of this paper is to explore if, and how, models can be developed to support identification and assessment of risks, including their dependencies, to inform their management. In particular our objectives are: (1) to examine the nature of systemic risks in supply chains; (2) to compare theoretical approaches to modelling systemic dependencies between risks; and (3) to explore the practical feasibility of modelling dependent risks

The assessment of risks

Although the process of managing risk will vary between organizations and objectives, there are a common set of principles. Figure 1 illustrates one representation of these principles.

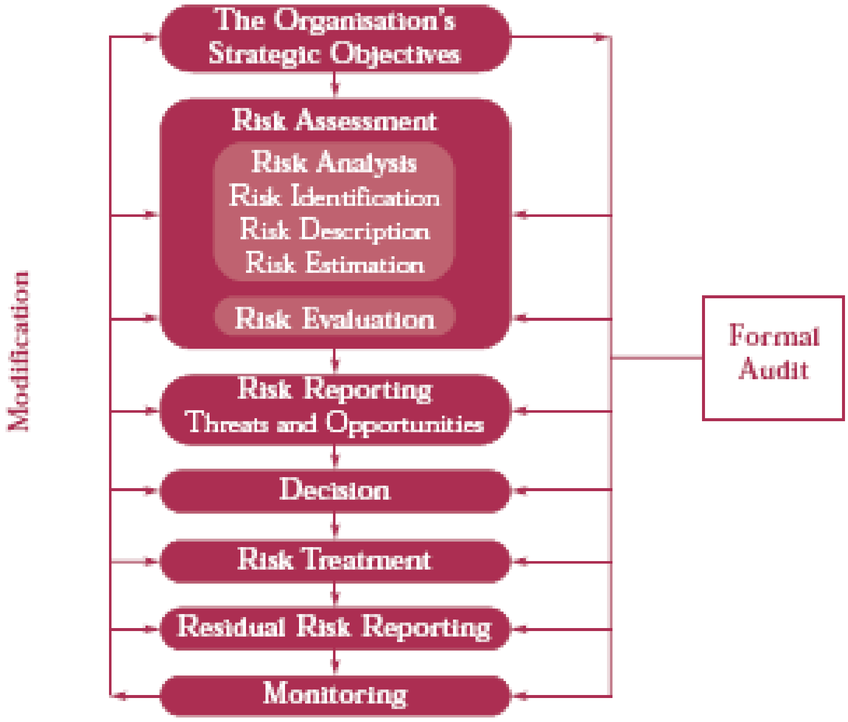

Figure 1 – The risk management process
(Source: A Risk Management Standard, published by IRM, ALARM, AIRMI, 2002)

Each stage in the process is necessary for effective management of risks. For example, the overall objectives of risk management must be consistent with the overall strategic goals and responsibilities of the organization to be effective and add value. The reporting and monitoring of risks are required to provide visibility of the key weaknesses so that actions can be planned and implemented as required to remove or mitigate risks. Risk documentation should allow for updating as new information comes available from monitoring of known risks and identification of the possible new risks corresponding to observed events or to anticipate events arising from changes in the organization or its operations.

The stage of assessing risks is core to the management process. Risk assessment involves identifying and estimating risks to support effective evaluation. The resource required to capture and estimate risks is non-trivial but worth the investment if it provides good quality data and analysis that can help an organization anticipate weaknesses and hence plan appropriately. For example, the identification of risks should be conducted by relevant groups of stakeholders who understand the aspect of the operations under consideration because they are the individuals who are able to identify potential risks for which valid and reliable data are required if value is to be generated by the analysis. The resource required to support risk identification and estimation (essentially data collection and analysis) will increase as the boundaries and the level of operational detail increases. Consequently, the relative proportion of the risk management budget allocated to the assessment stage will also grow as the complexity and scale of the operations increases because the absolute cost of the supporting processes (such as reporting) will be, to all extents and purposes, fixed.

Typically, the risk management literature and standards suggest relatively naïve approaches to gathering data about potential risks and estimating their effects. For example, there tends to be a focus on completing a data sheet which captures data about the description of the risk, the nature of its impact, a probability estimate, a severity rating and some aggregate measure of risk importance. A method such as Failure Modes and Effects Analysis (FMEA) might be used, and the data collected compiled as part of a Risk Register, which provides a convenient approach to managing the associated bureaucracy. The implication is that such approaches only allow single independent risks to be articulated with consequences for the coverage of all risks (as systemic dependent events may not be captured) and the estimation of their likelihood and impact.

There are multiple reasons for the simple approaches advocated for risk assessment. For example, the focus on the supporting elements of the risk management process including the construction of documentation such as Risk Registers in order to manage what is a complex activity where breadth rather than depth of coverage is emphasized. Another reason might be a lack of integration between the management and the modelling of risk which may have been more prevalent in a supply chain operational context than in others. In other areas, such as technical risk assessment, the role of modelling is more developed bringing benefits in terms of the value of information about potential risks due to better controlled data collection and analysis.

The importance of risk modelling

Ultimately a risk management process seeks to anticipate the risks that might be realized in future operations. The goal is to develop a method for perfectly identifying all risks, although realistically this may not be possible. Table 1 shows the different categories of risk status (known or unknown) from the perspectives of anticipating potential risks and the true state of the operational system.

Table 1 – Types of knowledge about adverse events

		Actual outcome of the event	
		Known	*Unknown*
Potential occurrence of an adverse event	*Known*	'Known-knowns' (focus on complexity of interactions)	'Known-unknowns' (focus on aleatoric uncertainty and complexity of interactions)
	Unknown	Denial or groupthink?	'Unknown-unknowns' (focus on epistemic uncertainty)

The added-value of good quality data collection is that we can move from simply identifying the 'known-knowns' (e.g. possible bias if people simply anchor on past observable events) to capture the 'known-unknowns' (e.g. creating future scenarios in which people think through possible hazards to an operation). A poor data collection process would fail to identify known risks, maybe by omission or maybe because of an expert or management bias (e.g. where it is believed that a management change will prevent future occurrences as a result of goal-seeking bias). Even with a good data collection process there may be some, so-called, 'unknown-unknowns'. The monitoring stage will allow the risk process to update if any information about these emerges. The goal of good data collection is to minimise the chance of missing the unknown-unknowns.

Modelling can support the identification and estimation of risk by providing a lens through which the operational system can be viewed. According to Mitchell (1993) a model can have two types of role: a model can represent a statement of beliefs and assumptions; or a model can be used as a device for prediction. In the former role, the model will help for the beliefs by forcing stakeholders to think through important details and gain shared understanding, while in the latter role a model will help focus beliefs to select problem-solving actions by translating real world inputs into outputs. There is scope for both types of modelling in risk management because the process of building the model is equivalent to the collection of data to identify and think through the impact of potential risks, while the constructed model then becomes a device which can be used to estimate or predict the effects of those risks on system operation or the organization.

There are obvious resource constraints on model building, for example, the time, costs and staff expertise required. Recognizing the trade-offs to be made between the scope and depth of the model required to support decisions, Phillips (1984) introduces the concept of requisite modelling which aspires to develop models that are fit-for-purpose. The classification of model dimensions given by Mitchell (1993) (e.g. actuality-abstraction, black-box-structural, off the shelf-purpose built, absolute-relative, passive- behavioural, private-public, part of system – whole system) provides a useful framework for positioning the type of modelling required for a given situation.

In the context of supply chain risk, there is opportunity for, and examples of, different types of models (e.g. Discrete Event Simulation, System Dynamics, Bayesian Belief Networks) being used in different ways (e.g. to understand consequences of downstream supply problems on upstream delivery, to understand time dynamics, to estimate risk of no or late supply). Not only do models provide a means of quantifying risks and/or measuring their effects, but many models have the capability of capturing the systemic effects we might expect in a supply chain (for example, exposure to common environmental factors, single supplier, international regulation). The simple risk identification methods such as FMEA and reporting mechanisms such as Risk Registers represent only independent risks and fail to capture dependencies that will exist within the system that is the supply chain. Consequently, the coverage of all potential risks will be incomplete and estimates of the impact of risks will be conservative. In addition, the shortcomings of risk calculations based on measures such as the Risk Priority Number, commonly used in FMEA and Risk Registers, are well known. However, more sophisticated models, such as Bayesian Networks, can provide more accurate estimates of risk by using inference grounded in sound theory.

Evaluation of alternative models for systemic risk

In this section we explore the different types of models that can be used to support risk analysis. In particular we explain how these methods capture the systemic nature of risks. The managerial decisions to be supported may involve the assessment of the one-off (re)design of a supply network or they may be part of an on-going process. The purpose of these models may be estimate the chance of occurrence of events (failures or their consequences) - usually by capturing logical inter-dependencies between variables – and/or to examine effects of adverse events on the performance of the supply network – often by replicating the physical flow of network.

The models selected in Table 2 all have relevance to risk analysis in context of supply networks. Some models (e.g. FMEA, FT/ET) are well established within the quantitative risk assessment tool set, while others (e.g. DES, SD) are well known for modelling supply chains. There are newer modelling technologies emerging (e.g. BBN, DBN) for which we now have the computing power to apply theory which has existed for some time (e.g. Bayes). Such models are finding applications in difference areas of risk analysis, including supply chains. Table 2 describes the relationship of these models to the purposes described above, stating their key assumption and provides references to selected relevant literature.

Table 2 – Characteristics of modelling approaches

Modelling approach	Level of study	Practical use in supply chain study	Previous research in supply chain risk
Discrete event simulation. (DES models are usually stochastic.)	Focus on the short-to-medium term operational level of decision making	Shows the effects of managerial interventions on system performance. Can be used to model supply chain processes at the operational level.	• Swaminathan et al (1998) • Saad and Kadirkamanathan (2006) • Kull and Closs (2008)
System dynamics / continuous simulation. (SD models are usually deterministic.)	Focus on the longer-term strategic level of decision making	Shows the effects of managerial interventions on system performance. Can be used to model the dynamic effects of (more or less complex) feedback loops on system performance.	• Chan and Chan (2006) • Helo (2000) • Wilson (2007) • Thongrattana and Robertson (2008) • Oehmen (2009)
Fault trees (FT) and event trees (ET). **Failure modes and effects analysis (FMEA).**	Focus on operational details.	Basic tools for risk assessment.	• Sinha et al. (2004) • Welborn (2007) • Trucco et al.(2008) • Kumar (2009)
Bayesian belief networks (BBN). **Dynamic Bayesian networks (DBN).**	All levels of decision making	Can be used to model both causes and effects of supply chain disruptions, where potentially adverse events are interlinked and interdependent.	• Nairn et al. (2002) • Pai et al. (2003) • Neil et al. (2005) • Kao et al. (2005) • Chin (2009) • Lee (2009) • Lockamy (2010) • Deleris and Erhun (2011)
Scenario planning.	Focus on the (very) long-term strategic level of decision making		• Van der Heijden (2005)

It is clear that all models are not equally appropriate for analysing supply chain risks. For example, the classical risk tools of FMEA and FT/ET are naive and so will miss important dependencies leading to an underestimation of risks. FMEA is an established method for exploring the entire sample space of risks in a systematic manner. However, the very structure of the FMEA process is that it only allows for independent and mutually exclusive events. To compensate for the statistical assumptions of independence in Fault Trees, it is possible to include so-called common cause failures and to estimate their chance of occurrence through some other stochastic model, usually a shock process. While this may provide a better statistical estimate of the risk, the process of arriving at this estimate tends not to be transparent. It is also possible to develop Dynamic Fault Trees to capture the changing profiles of system over time; however, such temporal changes tend to be related to discrete mission changes rather than a continuous, real-time process.

BBN, and increasingly DBN, have the ability to model system risks in the same way as a FT/ET, but they allow dependencies to be captured explicitly. While basic BBN are static models, DBN allow temporal relationships to be modelled, although again arguably by identifying suitable discrete time-slices that support requisite modelling.

While BBN provide a means of representing uncertainty in the parameters of the model and hence estimates of the probability of events, we argue that they are less able to cope with complex supply network structures than, for example, SD. SD, together with DES, provide useful simulation modelling approaches to understanding the effects of events of that might impact the supply flow, although we argue that SD has the ability to capture more complex dependencies between events. This capability to capture complexity better than alternative models such as BBN comes at the cost of modelling the system deterministically rather than stochastically.

Both BBN and SD approaches can be embedded within a modelling process that emphasizes the importance of model structuring as well as model quantification. Through the model structuring phase, stakeholders will be required to explore and identify potential risk events. However such exploration will usually be bounded by the agreed definition of the system under study. For example, the particular supply chain designs under consideration and a statement of the market in which operations will be run for the foreseeable future. In this sense we believe that BBN provides a useful approach for exploring the unknown future events that we are able to anticipate through rational analysis of the defined supply network configuration and operational environment.

Table 3 – Suitability of different modelling approaches

		Actual outcome of the event	
		Known (deterministic)	*Unknown (stochastic; inherently uncertain)*
Potential occurrence of an adverse event	*Known*	System dynamics	Discrete event simulation; (Dynamic) Bayesian belief network
	Unknown	Cognitive mapping?	Scenario planning

That is, BBN can be positioned primarily in the 'known-unknown' category of Table 3 (showing relationship between anticipated and realised risks). Both SD and BBN models can be represented graphically and can be developed by simple causal mapping and it is possible to use such models to explore alternative scenarios (e.g. supply designs, changing environments) to understand relative risks. Scenario planning is a natural qualitative tool for exploring strategic futures and hence thinking though risks associated with changes in the system assumptions by deliberately challenging these assumptions. In this sense, Scenario planning provides a mechanism for exploring (as far as one reasonably can) the ‘unknown-unknowns’ in Table 3.

Brief report of an exploratory case study

Over the last 18 months, we have been conducting a pilot case study with the management of a public-sector organisation in charge of implementing a large new distribution network for hospital medicines. The initial phase of this study (covering about 9 months) was concerned with the implementation of a centralised distribution network that formed a radical break from the previous decentralised form of organisation. This implementation project was characterised by high levels of both complexity (mainly because of the complexity of the distribution network and the large number of key stakeholders involved) and uncertainty (mainly because of the advanced nature of the robotics and surrounding technology and its large scale of implementation).

From a risk perspective, the key management tool before and during this phase was the use of detailed risk registers, as is common – and indeed often mandated – in these kinds of large and complex projects. However, according to our analysis, these risk registers have only been partially effective at best. As we have argued already, modelling should try to capture the essentially systemic nature of many risks, which risk registers often fail to do effectively. But in addition, this particular project offered a vivid example of the potentially crucial role of ‘unknown-unknowns’ – that is, those events that could hardly have been foreseen at the outset and that, even if one could conceive of them in principle, might not amenable to any kind of systematic estimation of probabilities.

The subsequent phase of our study, which is still on-going, is focusing on the move towards the routine operation of the new distribution network. In this phase, we are exploring the feasibility of a BBN modelling approach to complement the risk registers. Based on process maps we developed earlier, we aim to complete interviews with all relevant stakeholders, using a protocol informed by our selected BBN model principles, in order to qualitatively identify and structure the risks and the dependencies between them. We shall evaluate the BBN model in comparison with the risk register approach currently used. Note that this evaluation will focus on the process of identification and the understanding generated through model structuring and instantiation, but will not include a comparison of predictive ability.

Conclusion

In this paper we have aimed to increase awareness of, and provide approaches to, modelling systemic risks in supply chains and so address a gap identified in the literature. We have drawn on the existing theory of BBN and risk management, and identified a pilot case study in which these ideas are applied. In the longer term, we would intend that such a model might provide a tool for more effective management of supply chain risk.

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