How to choose mitigation measures for supply chain risks

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1. Introduction

The increased complexity of supply networks along with global dangers (e.g. financial crises and terrorist attacks) lead today's supply chains to face increasing exposure to risks (Wagner and Neshat 2012). Hence, managers recognise as a priority, the formulation of support systems allowing the selection of measures to mitigate such risks (Allen 2011). Among academic studies on support systems, Christopher and Peck (2004) and Neiger, Rotaru, and Churilov (2009) propose the application of supply chain re-engineering techniques for the identification of risk sources and risks. Although their approach gives useful insights for risk identification, it generally provides little more than general guidelines for the selection of mitigation measures. Further contributions on support systems, including Hallikas et al. (2004), Manuj and Mentzer (2008) and Tummala and Schoenherr (2006) apply the risk management process (in general terms: identify and assess risks and identify and prioritise mitigation measures) to the supply chain context. This approach allows managers to face risks in a more systematic way, enabling prioritising measures on the basis of the available resources and desired performance. However, these contributions suggest designing the supply chain risk management process in a qualitative and rather informal way. This approach also seems common in practice. In fact, according to Kruschwitz and Schockley (2010), the adoption of quantitative risk support systems in firms is low and risk management is the area in which companies could benefit the most from the use of analytical techniques.

Therefore, the present paper aims at filling this gap in academic literature and managerial practice by proposing a quantitative decision support system (DSS) to select appropriate mitigation measures for supply chain risks. The DSS is formulated according to a stochastic integer linear programming framework, which elaborates the supply chain managers judgements by way of utility functions and fuzzy-extended pairwise comparisons. The support system is theoretically grounded via a decision framework that includes relevant elements derived from the literature (i.e. risk sources, risks, mitigation measures and supply chain risk profile) and is consistent with the general risk management process. Guidelines for implementation complement the decision framework and the support system, including details on what risk management plans should include and when decisions should be made. The implementation of the DSS is portrayed via its application to the Artsana Group's supply chain. Artsana group is a manufacturer and distributor of baby apparel, toys, nursing, healthcare and cosmetic products. Chicco is their most famous brand worldwide.

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The main contribution of this paper is the provision of an analytical tool that enhances the decision-making process, in comparison with previous qualitative models. A further contribution of this work concerns the explicit modelling of the relationships between risks and their expected impact, as called for by Chopra and Sodhi (2004) and Ritchie and Brindley (2007). Therefore, the choice of mitigation measures is directly based on the types and expected importance of the risks identified and assessed. This is an advancement in comparison with previous studies analysing measures selection, where mitigation strategies and tactics are chosen on the basis of generic supply chain archetypes, e.g. efficient, responsive, risk hedging and agile supply chains (Manuj and Mentzer 2008). Additionally, we consider risk prioritisation and measure selection jointly to enable risk profile reduction, because conducting risk prioritisation and measures selection as two consecutive steps (Hallikas et al. 2004) may lead to incorrect results. The remainder of the paper is organised as follows. Section 2 introduces the theoretically grounded research framework, upon which the DSS is based. Section 3 includes the description of the support system proposed. The application of the DSS is illustrated in Section 4 by way of the industrial example. Finally, in Section 5, we include the discussion and draw the conclusions related to the present work.

2. Theoretical framework

In this section, we propose a decision framework, theoretically grounded in the previous literature on supply chain risk management, which identifies and describes the main elements of the supply chain risk management process and the relationships among them. This decision framework is the conceptual basis on which to formulate the analytical process of selecting mitigation measures for supply chain risks (Section 3). Consistently with Goodwin and Wright (2004), the framework (Figure 1) consists of decision nodes (triangles), chance events that are beyond control (circles) and their effects (arrows), state variables (boxes) and filters (trapezoids).

The decision framework represents the problem faced by a supply chain manager of choosing in advance appropriate measures to mitigate I relevant risks, denoted by the index i. Supply chain risks are those deemed relevant to the supply chain
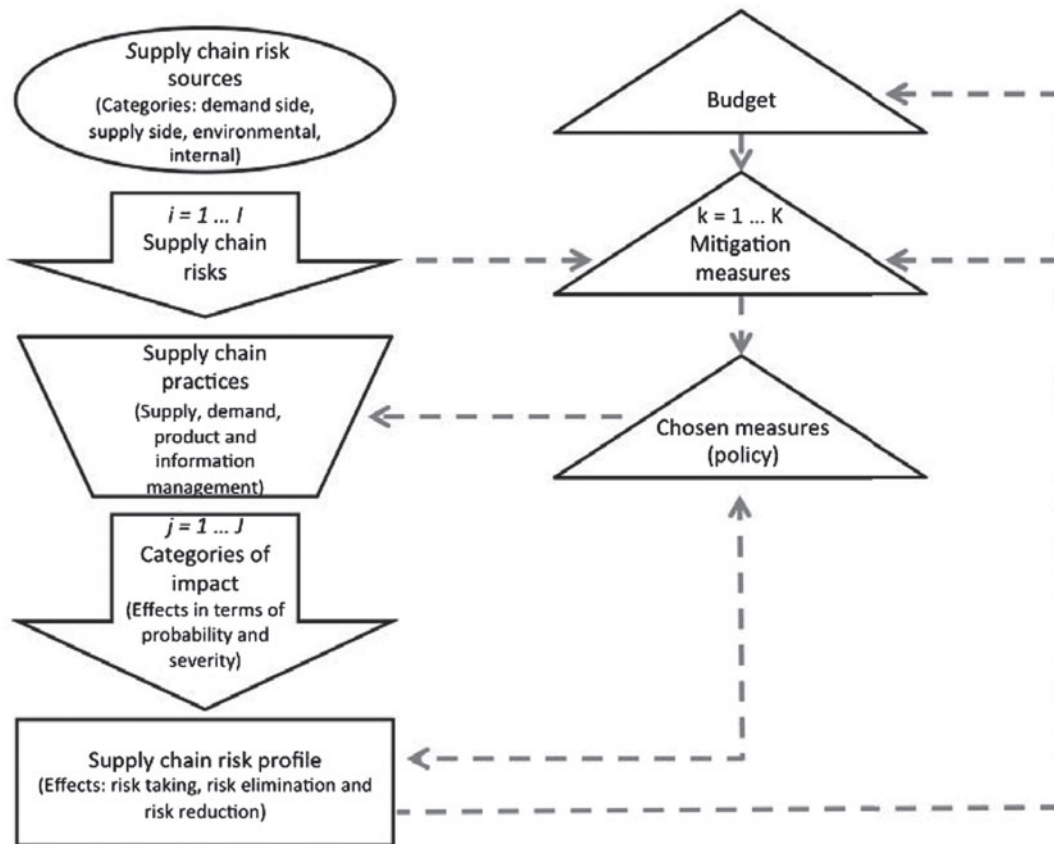

Figure 1. Decision framework.

in which the decision-maker operates. Risk is defined as the chance of danger, damage, loss, injury or any other undesired consequences (Harland, Brenchley, and Walker 2003).

Supply chain risks stem from risk sources, which are those variables that cannot be predicted with certainty and from which risks affecting supply chain outcome variables can emerge (Jüttner 2005; Faisal, Banwet, and Shankar 2006). Each risk source may originate many risks; in addition, simultaneous occurrence of many risk sources may result in one single risk. Specific risk sources can be identified from general categories suggested by the literature, i.e. demand side, supply side, environmental and internal risks (Christopher and Peck 2004; Jüttner 2005; Kleindorfer and Saad 2005; Wagner and Bode 2006). Risk identification may be carried out by using the supply chain re-engineering technique proposed by Christopher and Peck (2004) and Neiger, Rotaru, and Churilov (2009).

Supply chain risks are commonly described in terms of probability of occurrence and severity. The severity of a risk is the negative impact of the risk on performance, in case the risk occurs. Intuitively, the risk may affect J categories of impact, denoted by the index j, usually detailed after a set of firm performance indicators such as time, cost, quality and flexibility (Slack and Lewis 2002). Operational risks are characterised by high probability of occurrence and low severity (Chopra and Sodhi 2004) due to inherent uncertainties in supply, demand and cost (Tang 2006). Disruption risks are characterised by low probability of occurrence and high severity (Wagner and Bode 2008). Disruption risks arise from natural and man-made disasters such as earthquakes, floods, hurricanes, terrorist attacks or economic crises such as financial default of a supplier, currency appreciation or strikes (Tang 2006).

Previous literature suggests that the values of probability and severity of each risk vary on the basis of the current practices of the supply chain under consideration. This concept is closely related to supply chain vulnerability, which can be defined as susceptibility or predisposition to loss of a supply chain because of existing organisational or functional practices or conditions (Wagner and Bode 2006).

The decision-maker identifies K mitigation measures, denoted by the index k, on the basis of the types of risks faced by the supply chain. Mitigation measures are those in which the firm takes some action in advance of a disruption and so incurs the cost of the action regardless of whether a disruption occurs (Tomlin 2006). Mitigation measures influence supply chain practices, which in turn contribute to the reduction of the probability and severity of the risks under consideration. The decision-maker allocates a budget to be employed for the adoption of mitigation measures. Further costs could be borne by the supply chain in case the disruption occurs, but these would be considered as part of the impact of the disruption rather than in the preventive budget.

With the term 'policy', we refer to a combination of mitigation measures. A policy has a direct effect on supply chain practices in terms of supply management, demand management, product management and information management (Tang 2006). The effect of a specific policy on supply chain practices results in risk transfer, risk taking, risk elimination and risk reduction (Hallikas et al. 2004). The overall expected effect of a policy on supply chain risks could be assessed via the indicator 'supply chain risk profile'. The supply chain risk profile represents the degree of exposure of the supply chain to risks and can be measured as the expected value of severity of all risks faced by the supply chain (Kull and Talluri 2008; Samvedi, Jain, and Chan 2013).

For each policy, the decision-maker foresees the expected risk profile of the supply chain. The policy chosen would be the one leading to the largest reduction in the supply chain risk profile. If the risk profile is deemed unacceptable, the decision-maker can revise both the budget available for the preventive risk management process and the mitigation measures taken under consideration.

Finally, we would like to emphasise how the proposed decision framework is consistent with the previous contributions that apply the risk management process to mitigate supply chain risks (Hallikas et al. 2004; Manuj and Mentzer 2008; Tummala and Schoenherr 2006). Risk identification is taken into account in the analysis of risks and risk sources. Risk assessment is included in the evaluation of the supply chain risk profile on the basis of the values of probability of occurrence and severity associated to the relevant risks. Identification and prioritisation of measures are performed via a risk profile reduction strategy under a budget constraint, as described in greater level of detail in Section 3.

3. Decision support system

In this section, we propose a DSS for supply chains based on the risk management process. The support system identifies the combination of mitigation measures leading to the greatest reduction in the supply chain risk profile under a budget constraint. The supply chain risk profile is calculated as the expected value of the impact of all risks. The decision-maker, for each policy and each risk, expresses the values of probability and severity that are used to calculate the supply chain risk profile. Each severity value is based on the assessment of severity for each one of the impact categories affected by the risk. These assessments are then combined together by weights determined via fuzzy pairwise comparison.

3.1 *Introduction and related work*

We consider the problem faced by a supply chain manager of choosing a set of measures among K available, to mitigate I relevant risks influencing J categories of impact. According to the decision framework described in Section 2, the decision problem can be formulated as the *minimisation of supply chain risk profile through the selection of a set of mitigation measures on the basis of a given budget* available to the decision-maker. The formal formulation of this problem is detailed in para 3.2.

Previous studies adopting the risk management process in the supply chain field include Hallikas et al. (2004), Manuj and Mentzer (2008) and Tummala and Schoenherr (2006). Hallikas et al. (2004) suggest prioritising risks on the basis of their values of severity and probability of occurrence and assigning appropriate mitigation measures to those risks that are deemed to be critical. Their approach has been operationalised by Tummala and Schoenherr (2006). Manuj and Mentzer (2008) classify supply chains on the basis of the supply chain types as follows: efficient, responsive, risk hedging and agile supply chains. They extend the approach of Hallikas et al. (2004) by choosing mitigation measures not only in relation to the values of severity and probability of risks but also on the basis of the type of supply chain under consideration.

The support system that we propose to address the decision problem combines the use of utility functions and fuzzy-extended pairwise comparison (derived from the analytic hierarchy process) under a stochastic integer linear programming framework. In comparison with previous studies, the support system selects mitigation measures on the basis on their expected contribution in terms of reduction of supply chain risk profile.

The analytic hierarchy approach (AHP) has been previously used in decision-making processes taking into account risks, but mostly in deterministic settings. Kumar Dey (2002) combines AHP and decision tree approach to assess alternative responses to project risks. Chan et al. (2008) formulate a global supplier selection problem that includes risk factors. Their selection methodology is based on a fuzzy-extended AHP approach. AHP has also been previously combined with linear programming. For example, Sharma and Dubey (2010) integrate AHP with a linear programming knapsack formulation to evaluate multiple sourcing decisions.

3.2 *A linear programming formulation*

The set of mitigation measures available to the decision-maker is $\mathcal{M} = \{1, \ldots, K\}$ and k is the index used to denote a measure. An expected implementation cost c_k is associated to each measure k. Any feasible combination of measures is defined as policy, which is denoted by the index π and indicates a subset of the set, $\mathcal{M}$. The set of mitigation measures included under the policy π is $\mathcal{M}(\pi)$. It is important to note that the policies are mutually exclusive. The set of the available policies is $\mathcal{P} = \{1, \ldots, \Pi\}$. If all the possible combinations of measures are feasible the set $\mathcal{P}$ is defined as the power set of $\mathcal{M}$ and has cardinality 2^K. If the costs of measures are independent, the cost c_π can be computed as the sum of the costs of all the measures included under the policy, expressed as: $c_\pi = \sum_{k \in \mathcal{M}(\pi)} c_k$. Supply chain practices completely mediate the effects of each policy π on the risk profile, denoted by v_π. In para 3.3, we explain how to calculate the values of v_π from the judgements of a decision-maker on the relevant risks and their categories of impact. Assessing the effect of a combination of measures, i.e. a policy on the supply chain risk profile instead of evaluating the effect of various measures separately allows us to capture whether a joint adoption of more than one measure leads to a reduction of risk profile which is higher (synergy), the same or lower than the reduction attributable to the implementation of these measures separately. The decision variable associated to each policy π is $x_\pi \in \{0, 1\}$, taking the value 1 if the policy is selected for implementation and 0, otherwise. The decision problem aims at identifying an optimal policy π^*, which minimises the level of supply chain risk profile subject to the following constraints: (1) only a single policy can be chosen at a time; and (2) the cost of the policy chosen should be less or equal to the preliminary budget b set by the decision-maker. Hence, the decision problem can be formulated according to an integer linear programming framework as follows:

$$
\begin{aligned}
\underset{x_\pi}{\text{minimise}} \quad & \sum_{\pi \in \mathcal{P}} x_\pi v_\pi \\
\text{subject to} \quad & \sum_{\pi \in \mathcal{P}} x_\pi = 1 \\
& \sum_{\pi \in \mathcal{P}} x_\pi c_\pi \leq b \\
& x_\pi \in \{0, 1\}.
\end{aligned}
$$

Solving the integer linear programming problem leads to the identification of the optimal policy π^* and its associated set of mitigation measures $\mathcal{M}(\pi^*)$ that should be implemented by the decision-maker. The value of the objective function, when $x_{\pi^*} = 1$ represents the expected supply chain risk profile when the optimal set of measures is implemented.

3.3 *Determining the supply chain risk profile*

This section focuses on how to calculate the risk profile in terms of supply chain exposure to risks. The set of risks that the decision-maker needs to face is $\mathcal{R} = \{1, \ldots, I\}$ and i is the index used to denote a risk. Risks influence the set of impact categories $\mathcal{C} = \{1, \ldots, J\}$, where j is the index used to denote an impact category. The weight $w_j \in [0, 1]$ defines the relative importance to the decision-maker of the impact category, j in comparison with the other categories of impact. In para 3.4, we explain how to assess the weights w_j on the basis of the application of fuzzy-extended pairwise comparison to the judgements expressed by a decision-maker. The function $f : \mathcal{R} \to \mathcal{C}$ associates each risk i to a category of impact j. We assume that each category of impact (an element of $\mathcal{C}$) can be affected by multiple risks (elements of $\mathcal{R}$), but each risk i can influence only a specific category of impact j. This assumption allows us to provide a simpler formulation of the problem without compromising its practical contribution. In fact, if a risk generates negative effects on many categories of impact, it is always possible to isolate the contribution of the risk on a given category via the definition of a specific sub-risk. This assumption implies that the function f is a surjection and thus it is possible to define $\mathcal{R}(j) = \{i \in \mathcal{R} | f(i) = j\}$ as the set of all the risks influencing the same category of impact j.

The degree of exposure of each risk i when the policy π is implemented is captured by its probability of occurrence, denoted by $p_{i\pi} \in [0, 1]$, and its severity, denoted by $s_{i\pi} \in [0, 1]$. Each value of severity $s_{i\pi}$ is assessed from the decision-maker's judgements as follows. The decision-maker indicates a value of maximum likelihood of impact $l_{i\pi}$ for risk i when the policy π is implemented. This is expressed in the most adequate unit of measurement to represent the operational performance on which the risk i has an impact, e.g. hours of delay for time-based performance and percentage of faulty products in a lot for quality-based performance. The measurement scale of $l_{i\pi}$ is common for all the risks affecting the same category of impact of risk i and thus the set of possible values of maximum likelihood of impact $l_{i\pi}$ can be denoted as $\mathcal{L}_{f(i)}$.[1] The decision-maker associates each $l_{i\pi} \in \mathcal{L}_{f(i)}$ to a $s_{i\pi} \in [0, 1]$ by defining j utility functions $u_{f(i)} : \mathcal{L}_{f(i)} \to [0, 1]$ (one for each category of impact). Hence $s_{i\pi} = u_{f(i)}(l_{i\pi})$ and $u_{f(i)}$ is a surjection. The utility functions $u_{f(i)}$ can also be interpreted as membership functions of fuzzy sets. In fact, given a fuzzy set $\mathcal{A}$, a membership function 'associates with each point in the space of points $\mathcal{X}$ a real number in the interval $[0, 1]$, with the value of $f_A(x)$ at x representing the grade of membership of x in A' (Zadeh 1965). If a single risk affects a category of impact, the base scale for the severity $s_{i\pi} = 1$ should correspond to the policy π such that $\mathcal{M}(\pi) = \{\emptyset\}$, i.e. no mitigation measure is taken. If more than one risk affect the same category of impact, then at least one of them should have $s_{i\pi} = 1$ as a base scale for severity when the policy π corresponding to $\mathcal{M}(\pi) = \{\emptyset\}$ is implemented.

For each risk i, it is possible to identify the weight $w_{f(i)}$, where the function $f(i)$ associates the risk to its corresponding category of impact. Depending on the policy under consideration, we can also identify the values of probability $p_{i\pi}$ and severity $s_{i\pi}$ associated to each risk. Multiplying weight, probability and severity together, we obtain the expected contribution of each risk to the supply chain risk profile. Summing the expected contributions of all risks, we obtain, for each policy π, the overall supply chain risk profile as follows:

$$v_\pi = \sum_{i \in \mathcal{R}} w_{f(i)}(p_{i\pi} s_{i\pi}).$$

Our definition of supply chain risk profile extends the integer linear programming formulation of the problem described in para 3.2 to a stochastic setting. The problem is concerned with the minimisation of the supply chain risk profile interpreted as the sum of the expected value of the severity of each risk.[2] Moreover, instead of the simple value of risk severities, we weight them on the basis of their impact on performance.

Since the values of probability are included only in the objective function of the problem and not in the constraints, there are no feasibility problems for this stochastic linear programming formulation (Sen and Higle 1999).

3.4 *Determining the weights for the categories of impact*

In this paragraph, we explain how to determine the weights w_j for the categories of impact $1 \ldots J$ by way of fuzzy-extended pairwise comparison. The relative importance of performance indicators for decision-makers is not constant, but varies on the basis of the specific product or client taken into account when expressing the judgement (Slack and Lewis 2002). Using fuzzy numbers to determine the weights for impact categories helps decision-makers in eliciting the potential range of relative importance of performance indicators. The width of the range is correlated to the breadth of different products offered or markets served by the supply chain under consideration. The notation of the proposed approach is based on Chiou, Tzeng, and Cheng (2005), Chan et al. (2008) and Locatelli and Mancini (2012), who adopt a fuzzy-extended analytic hierarchy process (AHP) methodology.

As a *first step*, we ask the supply chain manager to assess the importance of the category of impact m over the category of impact n for each of the members of the set $\mathcal{C} = \{1 \ldots J\}$. The triangular fuzzy number $\tilde{a}_{mn}$ is used to express the value

of the relative importance between the two categories of impact and can be described as a triplet of values $(a^l_{mn}, a^m_{mn}, a^u_{mn})$, representing respectively the smallest possible value, the medium possible value and the largest possible value. In general, $a^l_{mn} \leq a^m_{mn} \leq a^u_{mn}$, with the special case $a^l_{mn} = a^m_{mn} = a^u_{mn}$ denoting by convention a non-fuzzy number, also called crisp. The triangular fuzzy number $\tilde{a}_{mn}$ is characterised by a membership function $\mu(x|\tilde{a}_{mn})$, which assigns to each value of the real line a grade of membership ranging between 0 and 1 and defined as follows:

$$\mu(x|\tilde{a}_{mn}) = \begin{cases} (x - a^l_{mn})/(a^m_{mn} - a^l_{mn}) & \text{for } x \in [a^l_{mn}, a^m_{mn}] \\ (a^u_{mn} - x)/(a^u_{mn} - a^m_{mn}) & \text{for } x \in (a^m_{mn}, a^u_{mn}] \\ 0 & \text{otherwise.} \end{cases}$$

Given $\alpha \in \mathbb{R}^+$ and two triangular fuzzy numbers $\tilde{a}_{mn} = (a^l_{mn}, a^m_{mn}, a^u_{mn})$ and $\tilde{b}_{mn} = (b^l_{mn}, b^m_{mn}, b^u_{mn})$, the fuzzy sum, the fuzzy subtraction, the multiplication between two fuzzy numbers, the multiplication between a real number and a fuzzy number and the fuzzy inverse can be, respectively, defined as follows:

$$\tilde{a}_{mn} \oplus \tilde{b}_{mn} = (a^l_{mn} + b^l_{mn}, a^m_{mn} + b^m_{mn}, a^u_{mn} + b^u_{mn});$$
$$\tilde{a}_{mn} \ominus \tilde{b}_{mn} = (a^l_{mn} - b^l_{mn}, a^m_{mn} - b^m_{mn}, a^u_{mn} - b^u_{mn});$$
$$\tilde{a}_{mn} \otimes \tilde{b}_{mn} = (a^l_{mn} b^l_{mn}, a^m_{mn} b^m_{mn}, a^u_{mn} b^u_{mn});$$
$$\alpha \otimes \tilde{a}_{mn} = (\alpha a^l_{mn}, \alpha a^m_{mn}, \alpha a^u_{mn});$$
$$\tilde{a}^{-1}_{mn} = (1/a^l_{mn}, 1/a^m_{mn}, 1/a^u_{mn}).$$

Previous papers adopting a similar methodology (Chiou, Tzeng, and Cheng 2005; Chan et al. 2008) require the decision-maker to express crisp judgements, which are then fuzzified according to predetermined intervals. In this study, we allow the decision-maker to define the triplet of values determining the triangular fuzzy numbers. We propose this latter approach, since it has the advantage of capturing explicitly the fuzziness in the judgements of the decision-maker. The space of the judgements a^l_{mn}, a^m_{mn} and a^u_{mn} is defined as follows:

$$\mathcal{G} = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 2^{-1}, 3^{-1}, 4^{-1}, 5^{-1}, 6^{-1}, 7^{-1}, 8^{-1}, 9^{-1}\}.$$

When performance m is equally or more relevant than performance n, the values 1, 3, 5, 7 and 9 indicate, respectively, 'equally relevant', 'weakly more relevant', 'essentially more relevant', 'very strongly more relevant' and 'absolutely more relevant' with 2, 4, 6 and 8 taking intermediate values between two adjacent judgements. The reciprocal values 2^{-1}, 3^{-1}, 4^{-1}, 5^{-1}, 6^{-1}, 7^{-1}, 8^{-1} and 9^{-1} take the same meaning when performance n is more relevant than performance m. The fuzzy matrix $\tilde{A}$ that summarises the judgements expressed by the decision-maker over the relative importance of performance m over performance n follows, with m and n, respectively, indicating the row-index and the column-index of the fuzzy matrix and J denoting the total number of categories of impact.

$$\tilde{A} = \begin{pmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1J} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{J1} & \tilde{a}_{J2} & \cdots & 1 \end{pmatrix} = \begin{pmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1J} \\ 1/\tilde{a}_{12} & 1 & \cdots & \tilde{a}_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1J} & 1/\tilde{a}_{2J} & \cdots & 1 \end{pmatrix}$$

As a *second step*, we use the geometric mean technique to compute the fuzzy weights in accordance to Buckley (1985), an approach also used by Chiou, Tzeng, and Cheng (2005). We denote by $\tilde{r}_m$ the geometric mean over the fuzzy comparison value of category of impact m, which still indicates the row-index of the fuzzy matrix. The fuzzy weight of category of impact m is described by $\tilde{w}_m = (w^l_m, w^m_m, w^u_m)$, where the values of w^l_m, w^m_m and w^u_m represent the lower, middle and upper values of the fuzzy weight of the category of impact m. The fuzzy weights can be computed by using the following formulas, which are based on the definition on operations on fuzzy numbers described previously:

$$\tilde{r}_m = (\tilde{a}_{m1} \otimes \tilde{a}_{m2} \otimes \ldots \otimes \tilde{a}_{mJ})^{1/J};$$
$$\tilde{w}_m = \tilde{r}_m \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \ldots \oplus \tilde{r}_J)^{-1}.$$

As a *third and final step*, we convert each fuzzy weight $\tilde{w}_m$ into its corresponding crisp value w^c_m using the centre-of-area-approach described by Zhao and Govind (1991) and applied for instance by Tzeng and Teng (1993). The values of w_m used in para 3.3 are obtained by normalising the corresponding values of w^c_m over the interval [0, 1]. The formulas used are as follows:

$$w_m^c = \frac{w_m^l + w_m^m + w_m^u}{3};$$

$$w_m = \frac{w_m^c}{\sum_{j=1}^{J} w_j^c}.$$

4. Industrial example: Artsana Group's supply chain

This section includes the application of the decision framework and support system to the Artsana Group (also known as Artsana), a manufacturer and distributor of baby care products. Its most famous brand is Chicco and its turnover almost reached €1 500 millions in 2010 (Artsana Group 2012). Meetings involving divisional supply chain directors, the quality management and the distribution logistics functions are arranged in the company every three months to discuss supply chain risk management issues. However, the risk management process in Artsana is relatively unstructured and the management is interested in implementing a support system to formalise measure selection to mitigate supply chain risks.

More specifically, we apply the support system to the divisional supply chain of Artsana managing products, in the nursery category along with strollers and feeding accessories, e.g. highchairs and steriliser systems. These products are grouped together due to the similarity of their supply chain processes. Their components are sourced globally, mostly from the far-east, and the finished products are then assembled in Europe-based plants. Additionally, they are subject to the same quality and safety standards. Data used for this industrial example have been collected via face-to-face meetings with the divisional supply chain director. Some data of this example have been scaled in order to protect Artsana's confidentiality. This case is exclusively used to illustrate the application of our support system and the reader should not draw conclusions on Artsana's current management practices based on this example.

For illustration purposes, we apply the support system to an area limited in scope: the global sourcing process of components. Due to Artsana's wide product range, the volume procured for each component is so small that dual sourcing is usually unfeasible. This exposes the global sourcing process to supply continuity risks (Lockamy and McCormack 2009; Colicchia, Dallari, and Melacini 2010). Therefore, the divisional manager is planning to allocate a budget of €400,000 a year to invest in measures to mitigate potential risks arising from this area.

Three main risks were identified in relation to the global sourcing process:

(1) *Disruptions in the global supply of goods*, stemming from suppliers own logistics processes and from international maritime shipping, associated with unforeseen security checks and European port workers' strikes.
(2) *Congestions in the suppliers' production process when accommodating additional orders of components*, stemming from unpredictable surges in demand of finished products. Limited capacity of some of the suppliers is also a source for this risk.
(3) *Glitches and malfunctions in the suppliers' production process*, leading to poor conformance of end products to specifications. Although the effects of this risk arise in the final assembly stage, these are mostly associated with poor quality of the components used in the assembly.

Risk (1) and risk (3) influence the impact categories 'time' and 'quality', respectively. Risk (2) has a direct effect on 'flexibility' but also a minor indirect effect on 'quality' since suppliers accommodating additional orders of components need to increase their production rate in such way that it could lead to a negative impact on the quality of products.

Artsana identified four main measures to deal with the risks described above:

(1) *Dual international transport.* A single order is split and allocated to two carriers with different destination ports. This measure reduces the probability of disruptions in supply.
(2) *Additional auditing on suppliers production capacity.* Auditors check whether the suppliers capacity dedicated to Artsana's products corresponds to the contractual one. This measure reduces the severity and the probability of disruptions in supply and the severity and the probability of congestions in the suppliers' production process, with reference to both flexibility and quality impact.
(3) *Collaborative planning.* The adoption of information technology to share production plans between Artsana and its suppliers reduces the severity and the probability of disruptions in supply and the severity and the probability of congestions in the suppliers' production process, with reference to both flexibility and quality impact.
(4) *Tougher checks of component quality against specification.* This measure reduces the severity of the impact on quality associated to congestions in the suppliers' production processes, along with the probability and severity of glitches in the suppliers' production process.

Table 1. Fuzzy pairwise comparison and final weights of impact categories.

| | Fuzzy comparison | | | Weight |
	Time	Flexibility	Quality	w_j
Time	$(1, 1, 1)$	$(1/6, 1/3, 1)$	$(1/9, 1/7, 1/4)$	0.09
Flexibility	$(1, 3, 6)$	$(1, 1, 1)$	$(1/7, 1/5, 1/3)$	0.17
Quality	$(4, 7, 9)$	$(3, 5, 7)$	$(1, 1, 1)$	0.74

Table 2. Utility function for the category of impact 'time' in terms of weeks of delay.

$l_{i\pi}$ (weeks)	$l_{i\pi} \leq 1$	$1 < l_{i\pi} \leq 2$	$2 < l_{i\pi} \leq 3$	$3 < l_{i\pi} \leq 4$	$l_{i\pi} > 4$
Severity $s_{i\pi}$	0	0.2	0.4	0.6	1

Table 3. Utility function for the category of impact 'flexibility' in terms of percentage of unsatisfied change of production capacity requested.

$l_{i\pi}$ (%)	$l_{i\pi} \leq 5\%$	$5\% < l_{i\pi} \leq 25\%$	$25\% < l_{i\pi} \leq 35\%$	$35\% < l_{i\pi} \leq 40\%$	$l_{i\pi} > 40\%$
Severity $s_{i\pi}$	0	0.1	0.5	0.8	1

Table 4. Utility function for the category of impact 'quality' in terms of percentage of non conformities.

$l_{i\pi}$ (%)	$l_{i\pi} \leq 2\%$	$2\% < l_{i\pi} \leq 3\%$	$3\% < l_{i\pi} \leq 4\%$	$4\% < l_{i\pi} \leq 5\%$	$l_{i\pi} > 5\%$
Severity $s_{i\pi}$	0	0.1	0.5	0.8	1

As all the measures can be adopted jointly, the total number of policies $\mathcal{P}$ available to the decision-maker is $2^4 = 16$. The costs of the policies c_π are calculated as full economic costs normalised over a solar year and appear in Table 5. The costs take into account the synergy of joint adoption of measures.

The decision-maker compared the relative importance of three impact categories: time, flexibility and quality. Artsana's supply chain serves a wide range of products to many different markets with various needs and requirements. Hence, the decision-maker, when comparing two indicators, was more comfortable in providing a range of relative importance rather than providing a single value. His judgements, expressed in terms of fuzzy numbers, and the final weights w_j, calculated as in para 3.4, are depicted in Table 1. The detailed calculations of final weights are described in the Appendix. The decision-maker was allowed to define fuzzy intervals where the middle value of the fuzzy number does not necessarily corresponds with the centre of the interval, as in the judgements comparing time and flexibility indicators. Quality is the most important category of impact for Artsana. In fact, even small defects in the end products may constitute potential threats for children and in turn could be extremely costly in terms of product recalls and damaging in terms of corporate reputation, as in the case of Mattel (The Economist 2007).

Maximum likelihood of impact for the categories time, flexibility and quality are respectively measured in Artsana in terms of weeks of delay, percentage of unsatisfied change of production capacity requested and percentage of nonconformities. Hence, the decision-maker determined three utility functions $u_{f(i)}$ to allow for the conversion of the values of maximum likelihood of impact into values of severity, ranging in the interval [0, 1]. These are defined in Tables 2–4.

For each combination of risk and policy, the supply chain divisional director formulated values of probability $p_{i\pi}$ and maximum likelihood of impact $l_{i\pi}$, then converted into $s_{i\pi}$ via utility functions. These took into account the potential synergy of joint adoption of measures. The values of probability and severity for each risk and policy, together with the weights of the impact categories have been used to determine the level of supply chain risk profile v_π for each policy π (Table 5). The detailed calculations of supply chain risk profile of Artsana can be found in the Appendix. As risk (2) has impact on 'flexibility' and 'quality', its contribution to each impact category has been taken into account separately via two sub-risks as detailed in para 3.3.

Table 5. Costs and supply chain risk profile for each policy.

Policy	Cost	Risk profile
{∅}	€ 0	0.312
{a}	€ 300,000	0.290
{b}	€ 80,000	0.193
{c}	€ 200,000	0.140
{d}	€ 140,000	0.185
{a, b}	€ 380,000	0.188
{a, c}	€ 500,000	0.137
{a, d}	€ 440,000	0.164
{b, c}	€ 210,000	0.129
{b, d}	€ 220,000	0.070
{c, d}	€ 340,000	0.047
{a, b, c}	€ 510,000	0.126
{a, b, d}	€ 520,000	0.065
{a, c, d}	€ 640,000	0.044
{b, c, d}	€ 350,000	0.036
{a, b, c, d}	€ 650,000	0.033

Finally, the linear programming model described in para 3.2 has been implemented as detailed in the Appendix. The resulting optimal policy π^* is {b, c, d}, its cost is € 350,000 and the corresponding risk profile is 0.036 (a 88.5% reduction from the initial level of risk profile). Due to the limited scope of this exemplary case, Table 5 can also be used for scenario analysis, for instance to understand the appropriateness of the supply chain risk budget. The budget available to the decision maker has been acknowledged to be adequate since a higher budget (€ 650,000) would only lead to a minor reduction in risk profile. Moreover, half of the budget available (€ 200,000) would lead to a risk profile of 0.140, which has been deemed as too high by the decision-maker.

In summary, we applied the DSS described in Section 3 to the global sourcing process of Artsana. The policy associated to the greatest reduction of supply chain risk profile under a budget constraint of € 400,000 includes the following measures: additional auditing on suppliers production capacity, collaborative planning and tougher checks of component quality against specification. Artsana's management regarded this DSS as extremely useful as it helps them in understanding the underlying relationships among risks and expected impacts. They also regard the extension of this approach to the risk management process of the whole supply chain as likely in the near future.

5. Discussion and conclusions

This paper provides a decision framework and a DSS to select appropriate mitigation measures for supply chain risks. The study proposes an analytical approach useful for both academicians and practitioners, since previous contributions rely mainly on qualitative frameworks and the management of supply chain risks in companies is often informal and unstructured (Thun, Druke, and Hoenig 2011). In comparison with the previous studies, the support framework and system proposed enhance the process of selecting mitigation measures for a given set of supply chain risks, with reference to four specific contributions.

First, we propose a decision framework (Figure 1) consistent with the supply chain risk management literature and with the academic practice, which enables an analytical formulation of the process and resolves inconsistencies of previous studies.

Second, we explicitly model the expected impact of alternative sets of mitigation measures on supply chain risks through the indicator 'supply chain risk profile' (Figure 1). This formulation allows us to obtain an optimal result in terms of a risk profile-minimising combination of mitigation measures, advancing previous models where measures are chosen on the basis of the supply chain type under consideration (Manuj and Mentzer 2008). Each supply chain type rigidly prescribes the use of specific mitigation measures. We relax this restrictive assumption by allowing for measures to be combined at the discretion of the decision-maker. This flexible setting potentially allows for measures impacting different supply chain practices, i.e. supply management, demand management, product management and information management (Tang 2006), to be used jointly.

Third, in our support system, we consider risk prioritisation and measure selection jointly to enable risk profile reduction. Previous studies adopting the risk management process prioritise risks before mitigation measures are chosen (Hallikas et al. 2004). This means that only a subset of risks deemed relevant according to some impact criteria are taken into account when

measures are selected. However, optimality for the two sub-problems (risk prioritisation and measure selection) does not necessarily imply the optimality for the problem as a whole. As an example, take into account an optimal policy for the whole problem that is particularly effective in mitigating a large number of operational risks. Due to their low severity, most of these risks may be classified as 'not relevant' and discarded in the risk prioritisation stage. In the measure selection stage, the policies will then be assessed on the basis of their effectiveness on the remaining 'relevant' risks. As most of the effectiveness of the optimal policy is associated to risks that did not make it to the second stage, a different policy may be chosen in the two-stage process.

Fourth, we show the applicability and the usefulness of the framework and support system to a real industrial example, the Artsana Group's supply chain.

The problem solved in the DSS can be briefly described as the reduction of supply chain risk profile through the selection of a set of mitigation measures on the basis of a given budget. An alternative formulation could analyse this problem the other way around: the cost minimisation of mitigation measures under the constraint of a supply chain risk profile that is less than or equal to an acceptable maximum level. Additionally, the probable occurrence of risks in our model makes it stochastic. This in turn means that alternative formulations of the objective function are possible, such as the minimisation of the worst-case absolute deviation from optimality. See Daniels and Kouvelis (1995) for an overview of this technique.

Our DSS is associated only with risk prevention in the supply chain. Further decision-making models could integrate risk prevention measures with contingent interventions that are adopted when disruptions occur.

Finally, although the DSS has been tested by way of an industrial example, the contribution of this study is mainly conceptual. Further work should focus on empirical analysis to show how the general tools developed here could be enhanced in practice.

Notes

1. In our problem, we require the decision-maker to assess a risk for each policy on the basis of a single value of probability of occurrence and a single value of likelihood of impact. In case the number of risks is small, the decision-maker could provide multiple values of likelihood of impact along with their associated values of probability. The contribution to the risk profile associated to that specific risk would be again determined in terms of expected value.
2. Note that the expected value operator does not require the independence of the events used in the calculation, in this case the independence of risks.

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Appendix 1. Calculations used in the industrial example

In this Appendix, we first describe how we computed the fuzzy weights in the industrial example, Artsana. We then present the calculations of Artsana's total supply chain risk. Finally, we describe the linear programming formulation employed for the industrial example. The weights of the indicators time, flexibility and quality are denoted, respectively, by w_1, w_2 and w_3. The calculations of each geometric mean $\tilde{r}_m$ over the fuzzy comparison value of category of impact m are based on the expert judgements depicted in Table 1 and calculated as follows:

$$\tilde{r}_1 = ((1 \cdot 1/6 \cdot 1/9)^{1/3}, (1 \cdot 1/3 \cdot 1/7)^{1/3}, (1 \cdot 1 \cdot 1/4)^{1/3}) = (0.26, 0.36, 0.63);$$
$$\tilde{r}_2 = ((1 \cdot 1 \cdot 1/7)^{1/3}, (3 \cdot 1 \cdot 1/5)^{1/3}, (6 \cdot 1 \cdot 1/3)^{1/3}) = (0.52, 0.84, 1.26);$$
$$\tilde{r}_3 = ((4 \cdot 3 \cdot 1)^{1/3}, (7 \cdot 5 \cdot 1)^{1/3}, (9 \cdot 7 \cdot 1)^{1/3}) = (2.29, 3.27, 3.98).$$

The fuzzy weights are then computed below:

$$(\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3)^{-1}$$
$$= ((0.63 + 1.26 + 3.98)^{-1}, (0.36 + 0.84 + 3.27)^{-1}, (0.26 + 0.52 + 2.29)^{-1})$$
$$= (0.17, 0.22, 0.33)$$
$$\tilde{w}_1 = (0.26/0.17, 0.36/0.22, 0.63/0.33) = (0.05, 0.08, 0.20);$$
$$\tilde{w}_2 = (0.52/0.17, 0.84/0.22, 1.26/0.33) = (0.09, 0.19, 0.41);$$
$$\tilde{w}_3 = (2.29/0.17, 3.27/0.22, 3.98/0.33) = (0.39, 0.73, 1.29).$$

Finally, each fuzzy weight $\tilde{w}_m$ is converted into its corresponding crisp value w_m^c and normalised value w_m as follows:

$$w_1^c = (0.05 + 0.08 + 0.20)/3 = 0.02;$$
$$w_2^c = (0.09 + 0.19 + 0.41)/3 = 0.03;$$
$$w_2^c = (0.39 + 0.73 + 1.29)/3 = 0.13;$$
$$w_1^c + w_2^c + w_2^c = 0.17;$$
$$w_1 = 0.02/0.17 = 0.09;$$
$$w_2 = 0.03/0.17 = 0.17;$$
$$w_3 = 0.13/0.17 = 0.74.$$

With reference to the risk profile calculation, we separately illustrate the contribution of each risk i and each policy π to the supply chain risk profile, indicated by $\Delta v_{i\pi}$. For each policy π, $\Delta v_{i\pi}$ is calculated as the product of the weight w_j, the severity $s_{i\pi}$ and the probability $p_{i\pi}$ associated to the risk i. The detailed calculations of $\Delta v_{i\pi}$ can be found in Tables A1, A2 and A3. For each risk i and each policy π, the total risk profile v_π is calculated as: $v_\pi = \Delta v_{1\pi} + \Delta v_{2\pi} + \Delta v_{3\pi}$. The values of v_π for each policy π are included in Table 5.

We now describe the linear programming model employed in the Artsana example. The objective function involves minimising the risk profile as detailed below:

$$\underset{x_\pi}{\text{minimise}}$$
$$0.312x_\emptyset + 0.290x_a + 0.193x_b + 0.140x_c + 0.185x_d + 0.188x_{a,b}$$
$$+ 0.137x_{a,c} + 0.164x_{a,d} + 0.129x_{b,c} + 0.070x_{b,d} + 0.047x_{c,d}$$
$$+ 0.126x_{a,b,c} + 0.065x_{a,b,d} + 0.044x_{a,c,d} + 0.036x_{b,c,d} + 0.033x_{a,b,c,d}$$

The model is subject to a constraint that specifies that only one policy π can be implemented:

$$x_\emptyset + x_a + x_b + x_c + x_d + x_{a,b} + x_{a,c} + x_{a,d} + x_{b,c} + x_{b,d} + x_{c,d}$$
$$+ x_{a,b,c} + x_{a,b,d} + x_{a,c,d} + x_{b,c,d} + x_{a,b,c,d} = 1$$

Table A1. Risk (1): Weight, severity, probability and contribution to risk profile.

Policy	Risk (1) – 'time'			
	w_j	$s_{i\pi}$	$p_{i\pi}$	$\Delta v_{i\pi}$
$\{\emptyset\}$	0.09	1.00	0.40	0.03
$\{a\}$	0.09	1.00	0.15	0.01
$\{b\}$	0.09	0.60	0.20	0.01
$\{c\}$	0.09	0.60	0.15	0.01
$\{d\}$	0.09	1.00	0.40	0.03
$\{a, b\}$	0.09	0.60	0.10	0.01
$\{a, c\}$	0.09	0.60	0.10	0.01
$\{a, d\}$	0.09	1.00	0.15	0.01
$\{b, c\}$	0.09	0.60	0.10	0.01
$\{b, d\}$	0.09	0.60	0.20	0.01
$\{c, d\}$	0.09	0.60	0.15	0.01
$\{a, b, c\}$	0.09	0.60	0.05	0.00
$\{a, b, d\}$	0.09	0.60	0.10	0.01
$\{a, c, d\}$	0.09	0.60	0.10	0.01
$\{b, c, d\}$	0.09	0.60	0.10	0.01
$\{a, b, c, d\}$	0.09	0.60	0.05	0.00

Table A2. Risk (2): Weight, severity, probability and contribution to risk profile.

Policy	Risk (2) – 'flexibility'			Risk (2) – 'quality'			$\Delta v_{i\pi}$
	w_j	$s_{i\pi}$	$p_{i\pi}$	w_j	$s_{i\pi}$	$p_{i\pi}$	
$\{\emptyset\}$	0.17	1.00	0.45	0.74	0.80	0.15	0.17
$\{a\}$	0.17	1.00	0.45	0.74	0.80	0.15	0.17
$\{b\}$	0.17	0.80	0.25	0.74	0.50	0.10	0.07
$\{c\}$	0.17	0.50	0.20	0.74	0.10	0.05	0.02
$\{d\}$	0.17	1.00	0.45	0.74	0.50	0.15	0.13
$\{a, b\}$	0.17	0.80	0.25	0.74	0.50	0.10	0.07
$\{a, c\}$	0.17	0.50	0.20	0.74	0.10	0.05	0.02
$\{a, d\}$	0.17	1.00	0.45	0.74	0.50	0.15	0.13
$\{b, c\}$	0.17	0.50	0.10	0.74	0.10	0.05	0.01
$\{b, d\}$	0.17	0.80	0.25	0.74	0.10	0.10	0.04
$\{c, d\}$	0.17	0.50	0.20	0.74	0.10	0.05	0.02
$\{a, b, c\}$	0.17	0.50	0.10	0.74	0.10	0.05	0.01
$\{a, b, d\}$	0.17	0.80	0.25	0.74	0.10	0.10	0.04
$\{a, c, d\}$	0.17	0.50	0.20	0.74	0.10	0.05	0.02
$\{b, c, d\}$	0.17	0.50	0.10	0.74	0.10	0.05	0.01
$\{a, b, c, d\}$	0.17	0.50	0.10	0.74	0.10	0.05	0.01

Table A3. Risk (3): Weight, severity, probability and contribution to risk profile.

Policy	Risk (3) – 'quality'			$\Delta v_{i\pi}$
	w_j	$s_{i\pi}$	$p_{i\pi}$	
$\{\emptyset\}$	0.74	1.00	0.15	0.11
$\{a\}$	0.74	1.00	0.15	0.11
$\{b\}$	0.74	1.00	0.15	0.11
$\{c\}$	0.74	1.00	0.15	0.11
$\{d\}$	0.74	0.50	0.05	0.02
$\{a, b\}$	0.74	1.00	0.15	0.11
$\{a, c\}$	0.74	1.00	0.15	0.11
$\{a, d\}$	0.74	0.50	0.05	0.02
$\{b, c\}$	0.74	1.00	0.15	0.11
$\{b, d\}$	0.74	0.50	0.05	0.02
$\{c, d\}$	0.74	0.50	0.05	0.11
$\{a, b, c\}$	0.74	1.00	0.15	0.02
$\{a, b, d\}$	0.74	0.50	0.05	0.02
$\{a, c, d\}$	0.74	0.50	0.05	0.02
$\{b, c, d\}$	0.74	0.50	0.05	0.02
$\{a, b, c, d\}$	0.74	0.50	0.05	0.02

Further, the budget constraint is as follows:

$$0 \cdot x_\emptyset + 300{,}000x_a + 80{,}000x_b + 200{,}000x_c + 140{,}000x_d$$
$$380{,}000x_{a,b} + 500{,}000x_{a,c} + 440{,}000x_{a,d} + 210{,}000x_{b,c}$$
$$220{,}000x_{b,d} + 340{,}000x_{c,d} + 510{,}000x_{a,b,c} + 520{,}000x_{a,b,d}$$
$$640{,}000x_{a,c,d} + 350{,}000x_{b,c,d} + 650{,}000x_{a,b,c,d}$$
$$\leq 400{,}000$$

Finally, we set the requirement that each decision variable is binary:

$$x_\pi \in \{0, 1\}$$