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Abstract

Selection of suppliers is very important for a strategic supply network (SN) design. This paper presents a novel multi-objective optimisation model for supplier selection and order allocation. In addition to a standard objective of total SN cost minimisation, two new objectives are considered: minimisation of suppliers' risk and maximisation of achievement of a manufacturer business strategy. Uncertainty in supply lead times and non-conformance rates of delivered components causes uncertainty in the SN cost objective. These parameters are described using imprecise linguistic terms and modelled using fuzzy numbers. Risk classification of suppliers is carried out using imprecise knowledge which is modelled using fuzzy If-Then rules and embedded in the risk objective. Various experiments are carried out to analyse the trade-off between the considered objectives and the impact of SN network parameters on the suppliers' selection and order allocation. The size of the problem that the model can handle is analysed also.

Keywords: Supply Network, Risk, Optimisation, Fuzzy sets

Introduction

Supplier selection has an important impact on costs incurred in SNs. The influence of the supplier selection increases with complexity of SNs and their operations. SNs suppliers bring different risks to SNs operations; they can deliver components earlier or later than required, quality of supply can be different than required, etc. An unanticipated increase in the SN cost is often caused by inadequately managed risk. In the circumstances of an expanding market and globalisation of SNs, a selection of the right suppliers has to be in line with a manufacturer's business strategies, regarding, for example, the number of suppliers, criteria used for selection, relationship with suppliers, etc (De Boer et al., 2001).

Initial approaches to supplier selection were typically formulated as a single-objective optimisation problem, which took into account the incurred cost only (Soukup, 1987, Weber et al., 1991). However, it has become obvious that different criteria for supplier selection have been relevant to SNs in different industries or lines of business. Some of the illustrative examples were given in (Shyur and Shih, 2006), but without an intention to provide an extensive list of industries and corresponding relevant criteria. A more formal approach was taken by Supply Chain Council who proposed a generic framework to be used to evaluate supplier performance considering four categories, including: (1) delivery reliability, (2) flexibility and responsiveness, (3) cost and (4) assets (Wang et al., 2004). Ho et al., (2010) reviewed multi-criteria optimisation models developed to enable simultaneous consideration of different quantitative and qualitative criteria for supplier selection. Since risk management has become an important part of a successful SN management (Choi et al., 2016, Heckmann et al., 2015, Zsidisin and Ritchie, 2008), considering risks in supplier selection has become important as well (Chan and Kumar, 2007).

This paper considers a complex real-world SN with one manufacturer, 19 first tier suppliers and 12 different produced commodities. The main characteristic of the SN are low volume production, long lead times, no inventory keeping principle and relatively high quality non-conformance of supplied components. In order to minimise the risk of supply shortages and supply delays, the safety stock and safety time are introduced. The former are kept for critical components which are susceptible to high non-conformance, while the latter are preventive measures for suppliers with consistent delivery problems. The model focusses on selecting suppliers and satisfying demand for one commodity only, that should be produced by the manufacturer on the requested due date.

Two main sources of uncertainty considered are lead time of supplied component and rate of non-conformance of supply with respect to the required quality. Historical data exist for some of the supplies only, and, even more, all the required data cannot be provided accurately. In such cases, it is advantageous to express these uncertainties using imprecise natural language terms, exploiting managerial experience and subjective judgement (Zimmermann, 2001). For example, lead time of a component can be *about* certain number of weeks or non-conformance of supply from a certain supplier can be *about* certain percentage of supply. It has been shown in a large body of literature that fuzzy sets theory provides a suitable framework for representing uncertainties in such decision-making problems (e.g., Petrovic and Akoz, 2008, Wulan and Petrovic, 2012).

The paper is proposing a new multi-objective approach to supplier selection and calculation of orders' quantities and times of ordering. Three objectives of different types, including minimisation of the total SN cost incurred with selected suppliers, minimisation of risk of the selected suppliers and maximisation of achievement of a manufacturer's business strategy are considered. The model includes the most often used objective of cost minimisation. However, some parameters including suppliers' lead times and non-conformance rates are uncertain and modelled using fuzzy numbers. Consequently, the total SN cost incurred becomes fuzzy too. It is calculated using fuzzy arithmetics. In order to consider it with other objectives simultaneously it is defuzzified into a corresponding scalar using a defuzzification method. As the second objective, the model considers a risk of selecting certain suppliers for supplying required components. This objective of risk minimisation is based on a supplier classification carried out by the manufacturer in practise. It includes a subjective judgement of the manufacturer expert on the component risk and supplier risk and is modelled using fuzzy If-Then rules. The rules are handled and transformed into a corresponding scalar using a fuzzy logic method, and then embedded in the objective. The manufacturer's business strategy classifies suppliers based on their statuses. It is included in the model as the objective of maximising achievement of the business strategy. This achievement depends on he selected suppliers and is modelled as a crisp number. All three objectives are normalised and combined into a single objective function. Various experiments are carried out to provide an insight into the objectives of supplier selection proposed and to analyse their impact on SN performance. The impact of the size of the problem on the computation time is analysed also.

The novelties of the proposed model are as follows. (1) The objectives considered are of different types consisting of uncertain parameters and uncertain knowledge on risk classification of suppliers and are handled using different methodologies including fuzzy arithmetics and fuzzy logic, respectively. (2) The model combines different sources of uncertainty including uncertainty in SN parameters such as lead times of suppliers and non-conformance rates of supplied components, and uncertainty in knowledge of component and suppliers' risk. (3) The model development is motivated by a real-world SN problem. (4) A new insight into impact of uncertainty in SN parameters, such as supplied components, suppliers' risks and the manufacturer's business strategy on SN performance is given.

The paper is organised as follows. Literature review is focused on multi-objective methods used in supplier selection problems and in particular on those which consider uncertainty in SN parameters, risk and a manufacturer's business strategy. The following sections introduce a problem statement and the description of the implemented model. Results analyses are described afterwards. The final section contains conclusions and outlines future research.

Literature review

Different multi-objective models to supplier selection have been introduced in the literature. We identified some models which considered uncertainty in criteria and, in particular, those that considered risk and business strategy as selection criteria (see Table 1).

One of the most often used methodologies is Data Envelopment Analysis (DEA), often referred to as the balanced benchmarking which measures the effectiveness of suppliers by calculating a performance measure ratio. DEA was applied in Forker and Mendez (2001) to identification of suppliers with lower cost and shorter delivery times, which were the two most often used criteria for supplier selection. In addition, the authors considered a criterion of selecting suppliers who could benefit from the Total Quality Management (TQM) development. A Monte Carlo based method combined with stochastic cross-efficiency DEA was presented in (Dotoli et al., 2015), who considered supplier selection in the presence of uncertainty in input, including quality of supplied components and suppliers' delivery reliability with respect to the scheduled times. Although DEA methodology has been successfully implemented for suppliers ranking, it is based on evaluation and comparison of suppliers' efficiency. However, it is only one of the criteria that can be used for supplier selection, while the practice faces many other issues.

A successful application of Analytic Hierarchy Process (AHP) to a supplier selection was presented in (Liu and Hai, 2005). This method was based on a decomposition of an initial decision problem and was focused on providing a comprehensive framework to analyse smaller and easier sub-problems of the supplier selection. They focused on objectively and subjectively defined criteria obtained by 60 employees of a real-world company. AHP models have commonly included fuzzy numbers, where fuzzy numbers have been used for modelling of the decision maker perception of criteria values. In Chen et al., (2006), linguistic values were used to describe profitability, relationship closeness, technological capability, conformance quality and conflict resolution of a given set of suppliers. A fuzzy AHP model was developed to rank the suppliers based on a difference between two fuzzy values.

Bottani and Rizzi (2008) extended multi-criteria decision making methodology by exploiting clusterization of suppliers and components in order to reduce a number of supplier alternatives which had to be assessed. Criteria values were modelled using fuzzy numbers. Sahu et al., (2016) developed a fuzzy VIKOR method to select suppliers considering resilience of suppliers as a selection criterion. A DEA non-parametric approach was adopted by Ng (2008), who developed a multiple criteria decision model for supplier selection. The weighted integer linear model (ILP) maximised suppliers' score which included quality of delivered products, distance, price, on-time delivery and supply variety. It was solvable by a spread sheet package, which made it easily applied by real-world companies. Cebi and Otay (2016) considered supplier selection and allocation problem using a fuzzy programming method. They were assigning different weights to fuzzy objectives.

In successful SNs management, consideration of risk factors has had a growing importance. However, most of the research carried out in the area of supplier selection treated risk as a criterion with a crisp value. Amorim et al. (2016) considered operational risk as a selection criterion which was focussed on lead time, inventory management of the suppliers and risk of low quality of service in food SNs. Ruhrmann et al., (2014) focused on an increasing companies outsourcing need. They proposed two-step approach to risk assessment in supplier selection process in low-wage countries. First step determined requirements for potential suppliers and second was used for identification and modelling of risks. A selection model proposed in (Paul, 2015), considered 18 selection criteria, where 14 were qualitative and 4 were quantitative in nature. Risk factors were incorporated in the criteria. The selection process was treated as a complex optimization problem, with different uncertainties defined in the supplier node. Chan and Kumar (2007) introduced a fuzzy extended AHP methodology for a global supplier selection problem. They considered criteria such as cost, quality service performance and risk. The risk factor was subjectively determined and included political stability, geographical location, economic condition and effect of terrorism. Sen et al., (2014) formulated problem as a scenario-based multi-stage stochastic optimization that considered uncertainties in a sudden drop in price, a price change or a new discount offer. Hamdi et al., 2016, presented two mixed integer linear programs to maximize profit and minimize the operational loss for a supplier selection problem in a make-to-order environment. Risk was modelled as stochastic scenario-based disruptions in supply. Two proposed models represented different decision-maker attitude towards risk, namely risk neutral and risk averse. Sawik (2017) proposed a mixed integer linear programming model (MILP) for a supplier selection in different scenarios depending on the appearance of disruptions. Govindan and Jepsen (2016) were using ELECTRE method to assign suppliers to risk categories considering probabilities of risks and their impacts.

Araz and Ozkarahan (2007) considered a business strategy in selecting suppliers. They used PROMETHEE method for ranking suppliers with respect to strategic partnerships into 4 categories: (1) to be selected as best strategic partners, (2) to be supported by development programs in order to increase cooperation, (3) to be selected to supply some products only and (4) not to be selected.

Described methods typically considered the risk of selecting a supplier as a criterion with a deterministic value. They do not explicitly consider uncertainty in knowledge of the subject expert which can be applied to supplier's risk evaluation. Furthermore, the business strategies are not taken into account when selecting suppliers. Finally, the optimisation models for supplier selection considered standard objectives such as minimisation of cost, supply time and/or risk involved. This paper is proposing a new supplier selection model which considers both uncertainty in risk and a business strategy of the manufacturer.

Table 1. Review of selected supplier selection models

Paper (year)	Methodology	Uncertainty in criteria	Deterministic risk	Uncertainty in risk	Business strategy
Forker and Mendez (2001)	DEA	×	×	×	×
Dotoli et al. (2015)	DEA and Monte Carlo simulation	✓	×	×	×
Liu and Hai (2005)	AHP	×	×	×	×
Chen et al. (2006)	Fuzzy TOPSIS	✓	×	×	×
Bottani and Rizzi (2008)	MCDM and Clustering	✓	×	×	×
Sahu et al. (2016)	Fuzzy VIKOR	✓	×	×	×
Ng (2008)	ILP	×	×	×	×
Cebi and Otay (2016)	Fuzzy Programming	✓	×	×	×
Amorim et al. (2016)	MIP	✓	✓	×	×
Ruhrmann et al. (2014)	Differential equations	×	✓	×	×
Paul (2015)	Fuzzy logic	✓	×	✓	×
Chan and Kumar (2007)	Fuzzy AHP	✓	×	✓	×
Sen et al. (2014)	MILP	✓	×	×	×
Hamdy et al. (2016)	MILP	✓	×	✓	×
Sawik (2016)	MILP	✓	✓	✓	×
Govindan and Jepsen (2016)	ELECTRE	✓	×	✓	×
Araz and Ozkarahan (2006)	PROMETHEE	×	×	×	✓

Problem statement

The model developed is motivated by a real-world SN problem of Bergen Engines (BE) introduced and discussed by Mr Aswathanarayana Nandakishore. BE produces medium speed engines for both the land and marine sectors. The manufacturer provides different types of engines, such as gas and diesel with various powers, number and configurations of cylinders. The manufacturer categorised components into four commodities handled by separate departments. The model presented in the paper, focuses on the Machining and Fabrication commodity, which has the highest visibility in their supply network. Supply lead times are relatively long, requiring 6-8 months for supply. The SN relevant to this department has relatively higher non-conformance rates, measured as the ratio of all non-conformed supplied components to all ordered components. Non-conformed components cannot be used and cause delays in the manufacturing processes. Safety stocks are kept for critical components supplied by suppliers with a high non-conformance rate.

The manufacturer developed a scorecard procedure for classifying suppliers with respect to risk into four categories: A, B, C and Z, as shown in Figure 1. The scorecard considers both component risk and supplier risk. Three factors influence a component risk value, including delegation of authority, component classification and component complexity. The delegation of authority considers who designs the component and who owns the intellectual right for this component. The component classification considers availability of this component from other manufacturers, while component complexity is determined by expert knowledge and can be *low*, *medium*, *high* or *super high*. These values are mapped into real values, 5, 10, 15 and 20, respectively. The sum of the scores from all three factors generates the component risk value in interval [0, 100]. The supplier risk is calculated using four factors: quality performance indicators which includes non-conformance rate and major issues found in the supplier audit, delivery performance indicators with respect to delivery time, ISO 9001 status and business dependence. The supplier risk is also presented as a scalar in interval [0, 100].

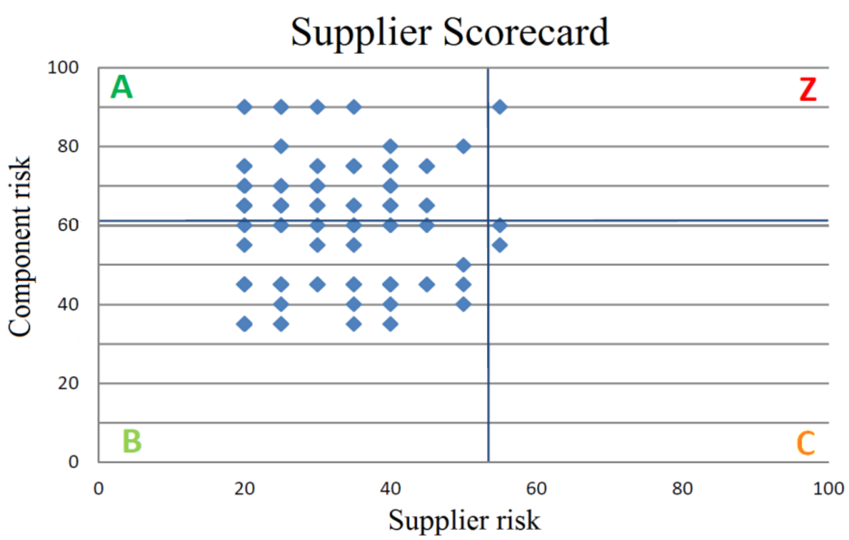

Figure 1 Supplier scorecard used by the manufacturer

The score card results also impact the manufacturer SN strategy which determines suppliers' statuses as G-growth, E-exit, M-maintain or N-new. G status is given to suppliers with increasing importance and with very good scorecards, E status to suppliers with a poor scorecard with whom the collaboration should finish, M status to suppliers with good scorecards with whom the collaboration should be continued and N status to potential future suppliers

By analysing the problem, the following objectives are identified: minimisation of cost incurred with selected suppliers, minimisation of risk of the selected suppliers and maximisation of the manufacturer's strategy achievement. They have to be considered simultaneously, but they are conflicting in nature. Cheaper suppliers can lead to the lower SN cost, while selecting them might cause an increase in risk. Also, a trade-off has to be made between the cost and achievement of the business strategy. For example, cheaper suppliers can be in the Exit sector, leading to the reduced SN cost, but a lower strategy achievement, while more expensive suppliers can be in Maintain, New or Grow sectors, which is in line with the manufacturer business strategy, but can increase the SN cost. Furthermore, suppliers in the four sectors can have different risks which bring into a conflict the objectives of risk minimisation and maximisation of strategy achievement.

Fuzzy multi-objective optimisation

The following notation is used:

Indices:

- $i = 1, \dots, I$ – Supplier
- $c = 1, \dots, C$ – Component

Input parameters:

- $\bar{B} = [B_1, \dots, B_C]$ – Vector of bill of material (BOM) which consists of the numbers of components 1, …, C required to build the engine
- $\beta_c^i = \begin{cases} 1 & if\ supplier\ i\ provides\ component\ c \\ 0 & otherwise \end{cases}$ – Component availability
- ft_c^i - Unit fine for early/late delivery of component *c* by supplier *i*
- fq_c^i - Unit fine for quality non-conformance of component *c* delivered by supplier *i*
- f - Fine paid by the manufacturer for each week of delay of delivering the engine
- m_c^i - Unit purchase cost of component *c* from supplier *i*
- h_c - Unit holding cost of component *c* for one week
- b_c^i - Minimum order quantity of component *c* from supplier *i*
- a - Assembly time of the engine (in *weeks*)

- T - Due date of delivery of the engine (in *weeks*)
- rp_c - Risk of component *c* determined by the manufacturer
- rs^i - Risk of supplier *i* determined by the manufacturer
- status of supplier $i \in \{E, M, N, G\}$ where:
  - E – Exit supplier
  - M – Maintain supplier
  - N – New supplier
  - G – Grow supplier
- $\tilde{L}_c^i = (l_1, l_2, l_3, l_4)$ – Trapezoidal fuzzy lead time of component *c* from supplier *i*
- $\tilde{Q}_c^i = (q_1, q_2, g_3, q_4)$ - Trapezoidal fuzzy non-conformance rate of component *c* from supplier *i*

Decision variables:

- x_c^i – Quantity of component *c* to order from supplier *i*; $x_c^i > 0$ means that supplier *i* is selected to supply component *c*
- $y_c^i \in \{1, \ldots, (T - \mathrm{a} - 1)\}$ – Time of ordering component *c* from supplier *i*

Auxiliary variables:

- $\tilde{\varepsilon}_c^i$ - Expected delivery time of component *c* from supplier *i* (in *weeks*)
- $\tilde{d}_c^i$ - Delay of supply of component *c* from supplier *i* (in *weeks*)
- $\tilde{e}_c^i$ - Earlier delivery of component *c* from supplier *i* (in *weeks*)
- $\tilde{\Delta}$ - Delay of delivering the engine (in *weeks*)
- X_c - Safety stock for component *c*
- $\tilde{\mathrm{G}}_c^i$ - Quantity of good quality component *c* from supplier *i*
- $\tilde{w}$ - Total cost incurred for manufacturing the engine
- $\tilde{w}_c$ - Total cost of handling component *c*
- $\tilde{H}_c$ - Total holding cost of component *c*
- $\tilde{F}_c$ - Penalty cost for component *c* for late delivery or non-conformance
- $\tilde{\delta}$ - Delay cost paid by the manufacturer for delay in engine delivery
- r - Total risk
- $risk\_score_c^i$ - Risk score for component *c* delivered by supplier *i*
- Φ - Business strategy achievement
- $g(i)$- Penalty of supplier *i* with respect to business strategy achievement.

Treating uncertainty using fuzzy numbers

Two input parameters are uncertain including lead time of component *c* from supplier *i*, $\tilde{L}_c^i$, and non-conformance rate of component *c* supplied by supplier *i*, $\tilde{Q}_c^i$. They are often specified in practice using imprecise natural language terms. They are modelled by trapezoidal membership functions, defined by 4-touples $\tilde{L}_c^i = (l_1, l_2, l_3, l_4)$ and $\tilde{Q}_c^i = (q_1, q_2, q_3, q_4)$, which can be interpreted as follows, lead time is *around* l_2 and l_3, but definitely not earlier than l_1, and not later than l_4, or non-conformance rate is *around* q_2 and q_3 but definitely not smaller that q_1 and not larger that q_4. These fuzzy quantities Figure 2 represents fuzzy lead time $\tilde{L}_c^i$ and fuzzy non-conformance rate $\tilde{Q}_c^i$. Membership function of $\tilde{L}_c^i$ is defined as:

$$\mu(L_c^i) = \begin{cases} \dfrac{L_c^i - l_1}{l_2 - l_1} & \text{where } l_1 \le L_c^i < l_2 \\ 1 & \text{where } l_2 \le L_c^i \le l_3 \\ \dfrac{l_4 - L_c^i}{l_4 - l_3} & \text{where } l_3 < L_c^i \le l_4 \\ 0 & \text{otherwise} \end{cases}$$

Membership function $\mu(\tilde{Q}_c^i)$ is defined in the same way.

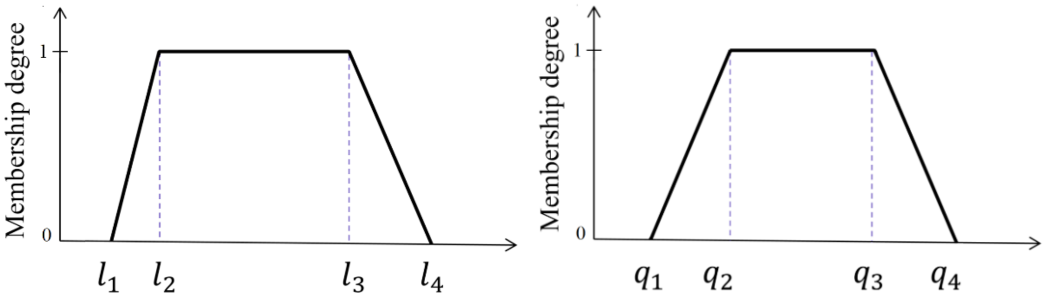

Figure 2 Graphical representation of fuzzy numbers $\tilde{L}_c^i$ and $\tilde{Q}_c^i$

Objectives

The following three objectives are defined.

Objective 1: *Minimisation of cost*

Different types of incurred costs are calculated as follows:

- Total holding cost $\widetilde{H}_c$ of delivered component *c* includes the holding cost of keeping the component *c* delivered too early and kept in stock, and the cost of keeping the component *c* delivered on time in the case when other components are delayed.

$$\widetilde{H_c} = h_c \sum_{i=1}^{I} (\tilde{e}_c^i + \max(\tilde{\Delta} - \tilde{d}_c^i, 0))\mathrm{x}_\mathrm{c}^\mathrm{i}$$

- Penalty cost $\widetilde{F}_c$ paid for component c is the sum of penalties paid by all the suppliers who did not supply component c on time or for non-conformance of supplied component c.

$$\widetilde{F}_c = \sum_{i=1}^{I} [\,(\tilde{e}_c^i + \tilde{d}_c^i)\mathrm{x}_\mathrm{c}^\mathrm{i} \, f t_c^i + \left(x_c^i - G_c^i\right) f q_c^i\,]$$

- Total cost $\widetilde{w}_c$ of handling supplied component c is the sum of purchasing cost of and holding cost of the component c, decreased by the penalty cost paid for component c.

$$\widetilde{w}_c = \sum_{i=1}^{I} x_c^i m_c^i + \widetilde{H}_c - \widetilde{F}_c$$

- Delay cost $\tilde{\delta}$ is the fine paid by the manufacturer to the customer for delays in delivery of the ordered engine. It is calculated by multiplying the total delay in weeks and the fine charged per week of delay.

$$\tilde{\delta} = \tilde{\Delta} f$$

Expected delivery time $\tilde{\varepsilon}_c^i$ of component c supplied by supplier i is the time at which component c should be supplied by supplier i, calculated as the sum of order time and lead time.

$$\tilde{\varepsilon}_c^i = y_c^i + \tilde{L}_c^i$$

Delay and earlier delivery of component c supplied by supplier i, $\tilde{d}_c^i$ and $\tilde{e}_c^i$, respectively, are calculated as the difference between the expected and the required time of delivery, $\tilde{\varepsilon}_c^i$ and $(T - a)$, respectively.

$$\tilde{d}_c^i = \max\left(\tilde{\varepsilon}_c^i - (T - a), 0\right) \times \min\left(x_c^i, 1\right)$$
$$\tilde{e}_c^i = \max\left((T - a) - \tilde{\varepsilon}_c^i, 0\right) \times \min\left(x_c^i, 1\right)$$

Total delay $\tilde{\Delta}$ presents a delay of the engine delivery and is equal to the maximum of all delays in supplies.

$$\tilde{\Delta} = \max_{i,c} \tilde{d}_c^i$$

Good component's quantity, $\widetilde{G}_c^i$, presents a quantity of component c supplied by supplier i that is suitable for use, and it is directly proportional to the supplied components and to the non-conformance rate.

$$\tilde{G}_c^i = x_c^i \tilde{Q}_c^i$$

Constraints

The following constraints are included in the model:

- Only supplier i which provides required component c can be taken into consideration.

$$x_c^i \beta_c^i = x_c^i, \qquad c = 1, \dots, C, \qquad i = 1, \dots, I$$

- Only components specified in the BOM are ordered

$$\min(x_c^i, 1) \leq \min(\mathrm{B_c}, 1), \qquad c = 1, \dots, C, \qquad i = 1, \dots, I$$

- An order quantity of component c from supplier i must not be smaller than minimum order quantity b_c^i.

$$x_c^i \geq b_c^i \times \min(x_c^i, 1), \qquad c = 1, \dots, C, \qquad i = 1, \dots, I$$

- Customer demand must be satisfied, and, therefore, the exact or higher numbers of components required in the BOM should be ordered.

$$\bar{B}_c \leq \tilde{\Gamma}_c, \qquad c = 1, \dots, C$$

where $\tilde{\Gamma}_c = \sum_{i=1}^{I} \tilde{G}_c^i$

Total cost $\tilde{w}$ is calculated as the sum of handling cost of all the components delivered by suppliers and the delay penalty paid by the manufacturer for the delay in engine delivery.

$$\tilde{w} = \sum_{c=1}^{C} \tilde{w}_c + \tilde{\delta}$$

Due to the fuzzy parameters, the total cost becomes fuzzy too. The fuzzy arithmetic operations and defuzzification of the fuzzy total cost into a scalar used in this objective are defined in Appendix. In this way, the objective of minimisation of fuzzy cost is mapped into the objective of minimisation of the corresponding crisp cost.

***Objective 2**: Minimisation of risk*

In practice, the manufacturer carries out the categorisation of suppliers as presented in Figure 1. It is included in the model as objective 2. We developed novel fuzzy rules to categorise suppliers into four risk categories A, B, C and Z, considering both component risk, rp_c, and supplier risk, rs^i, as follows:

Rule 1. If rp_c is *Low* and rs^i is *Low*

Then $risk\_score = 25$ (category B)

Rule 2. If $rp_c$is *High* and rs^i is *Low*

Then $risk\_score = 50$ (category A)

Rule 3. If $rp_c$is *Low* and rs^i is *High*

Then $risk\_ score = 75$ (category C)

Rule 4. If $rp_c$is *High* and $rs^i$is *High*

Then $risk\_ score =$ 100 (category Z)

Fuzzy terms *Low* and *High* risks are defined as fuzzy numbers presented in Figure 3, where the manufacturer's experts estimate boundaries of *Low* and *High* risks. Supplier/component risk 0 is definitely *Low* with the degree of belief 1, up to the risk equal to 65, with decreasing belief that the risk is *Low.* Similarly, supplier/component risk equal to 35 is *High* with degree of belief 0, with increasing degrees of belief, up to the risk of 100 that has the degree of belief equal to 1.

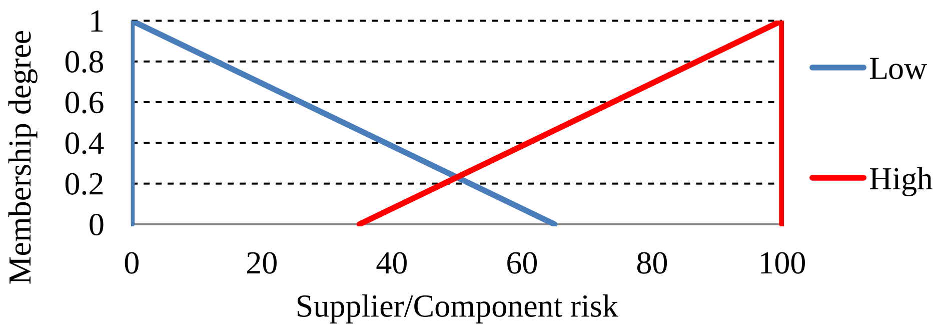

Figure 3 Component and supplier risks representation as fuzzy numbers

We allocated 4 different weights to the categories in the Then parts of the rules, with the lowest weight 25 for category B which includes *low* risk suppliers who supply *low* risk components, weight 50 for category A which includes *low* risk suppliers who supply *high* risk components, weight 75 for category C with *high* risk suppliers and *low* risk components and weight 100 to category Z with *high* risk suppliers and *high* components' risks.

Reasoning on these fuzzy rules is based on modified Takagi and Sugeno method (Takagi and Sugeno, 1985). In the first step, crisp inputs of component's and supplier's risk, rp_c and rs^i, respectively, are fuzzified, i.e. degrees of belief of their membership to fuzzy numbers *Low* and *High* in the If part of each rule are determined. For example, the corresponding degrees of belief in Rule 1 are $\mu_{Low}(rs^i)$ and $\mu_{Low}(rp_c)$. In the second step, the firing strength of the rule is calculated as $\mu_{Low}(rs^i) \times \mu_{Low}(rp_c)$. In the third step, the *risk_score* is calculated as the product of the category weight in the Then part of the rule and the rule firing strength. For example, the *risk_score* after firing Rule 1 is $25 \times \mu_{Low}(rs^i) \times \mu_{Low}(rp_c)$. These steps are repeated for each rule. Finally, the total $risk\_score_c^i$ is determined as the sum of *risk_scores* obtained in all fuzzy rules:

$$risk_{score_c^i} = 25 \times \mu_{Low}(rs^i) \times \mu_{Low}(rp_c) + 50 \times \mu_{High}(rs^i) \times \mu_{Low}(rp_c)$$
$$+ 75 \times \mu_{Low}(rs^i) \times \mu_{High}(rp_c) + \ 100 \times \mu_{High}(rs^i) \times \mu_{High}(rp_c)$$

The total risk scores for all possible component risk $rp_c \in [0, 100]$ and supplier risk $rs^i \in [0, 100]$ are presented in Figure 4.

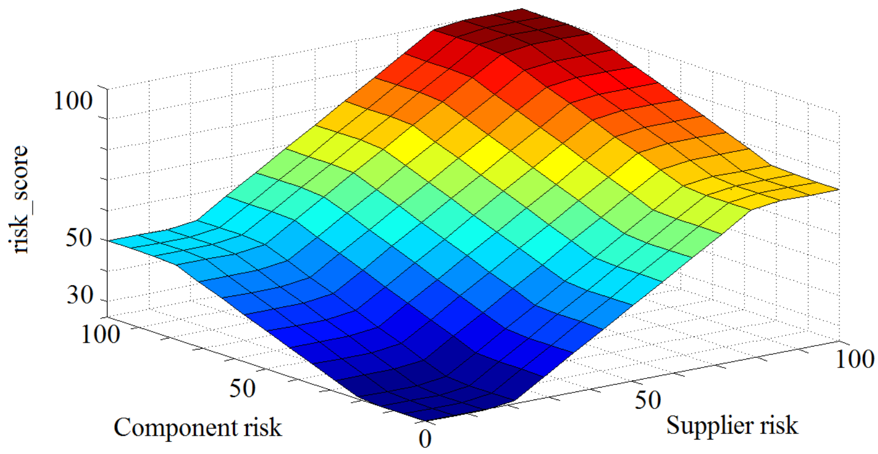

Figure 4 Total risk scores for all component and supplier risks in interval [0,100]

Objective 2 is defined to minimise risk as follows

$$r = \sum_{c=1}^{C} \frac{\sum_{i=1}^{I} risk\_score_c^i \times x_c^i}{\max(\sum_{i=1}^{I} x_c^i, 1)}$$

Risk associated with ordering a single component *c* is expressed as weighted average of risk scores of all suppliers selected to supply component *c*, where weights are equal to the ordered quantities. In this way, introducing another supplier for the same component will decrease the final risk, if the introduced supplier has a lower risk than already selected supplier. The fuzzy logic method used to determine *risk_score* for each component and supplier is incorporated and mapped into the crisp Objective 2.

Objectives 3: *Maximisation of business strategy achievement*

Objective 3 is introduced to maximise business strategy achievement. It is carried out by minimising penalty Φ of all suppliers with respect to the four suppliers' statuses, G-Grow, E-Exit, M-Maintain, N-New, described previously, as follows:

$$\Phi = \sum_{i=1}^{I}\sum_{c=1}^{C} g(i) \times \min(x_c^i, 1)$$

Function $g(i)$ penalises supplier i with status E, M, N or G, as follows:

$$g(i) = \begin{cases} 10 & \text{supplier } i \text{ has } E \text{ status} \\ 2 & \text{supplier } i \text{ has } M \text{ status} \\ 1 & \text{supplier } i \text{ has } N \text{ status} \\ 0 & \text{supplier } i \text{ has } G \text{ status} \end{cases}$$

Objective 3 is a crisp objective.

The three objectives are incommensurable and have different scales. Therefore, we normalised all three objectives into interval [0, 1] using the formula:

$$\frac{Objective\ value - Minimum\ value\ of\ Objective}{Maximum\ value\ of\ Objective - Minimum\ value\ of\ Objective}$$

We determined the minimum and the maximum values of all three objectives as follows. Minimum value of Objective 1 is the minimum cost incurred when only the one supplier with the lowest unit purchase cost is used for each required component. The perfect supplied quality is assumed, i.e., only the exact amount from $\bar{B}$ is ordered from the cheapest supplier. Delays and penalties are not considered. Maximum value of Objective 1 is the maximum cost incurred when only the supplier with the highest unit purchase cost is selected for each required component. The highest non-conformance rate of each supplier for the required component is assumed. The maximum penalty to be paid by the manufacturer is calculated assuming the longest possible lead times of all the considered suppliers. Also, it is assumed that the maximum holding costs of all the ordered components are incurred. Minimum value of Objective 2 is the minimum risk incurred when the supplier with the lowest risk of 25 is used for each required component only, and *risk_score* is 0. The maximum value of Objective 2 is obtained when only the supplier with the highest risk of 100 is used and *risk_score* is 1. Minimum value of Objective 3 is achieved when the minimum business strategy achievement is reached. In this case, it is assumed that for each required component, the selected supplier has the E status and has the maximum penalty 10. Maximum value of Objective 3 is achieved when the maximum business strategy achievement is reached. In this case, it is assumed that for each required component the selected supplier has the G status and has the minimum penalty 0.

The multiple objectives are combined in a single objective function, which is defined as the sum of the weighted normalised objective functions. It has to be minimised. This multi-objective decision making methods is referred to as Single Additive Weighting method (Hwang and Yoon, 1981). In this model, quantities of each component to be ordered from suppliers and times of ordering are found in such a way as to minimise the sum of the weighted normalised values of the three objectives.

A pseudo code of the proposed method is as follows.

Step 1. Find the minimum and the maximum values of all three objectives.

Repeat Steps 2 to 6 for each possible set of suppliers until the minimum sum of the weighted normalised values of the three objectives is found.

Step 2. Calculate the fuzzy cost incurred with a set of suppliers under consideration.

Step 3. Defuzzify the fuzzy cost into a crisp scalar to obtain a crisp value of Objective 1.

Step 4. Calculate the crisp risk of the considered set of suppliers, using the fuzzy If-Then rules to obtain the crisp value of Objective 2.

Step 5. Calculate the penalty of business strategy achievement for the considered set of suppliers to obtain the crisp Objective 3 value.

Step 6. Calculate the sum of the three weighted normalised objective values achieved with the considered set of suppliers.

Implementation

The single objective optimisation model is input into AIMMS (Advanced Interactive Multidimensional Modelling System). It handled it as a nonlinear optimisation model with integer decision variables, x_c^i and y_c^i. The model is implements using a lap-top with Intel(R) Core(TM) i7-5500U CPU 2.40 GHz processor and 16 GB RAM. Furthermore, a fuzzy logic toolbox of Matlab is used for the implementation of Objective 2, i.e., the fuzzy If-Then rules. The generated risk scores of all the suppliers are stored in a look up table and used by the AIMMS model for Objective 2.

Analysis of results

Sample real world data required in the model are collected from the manufacturer. Due to confidentiality issues and absence of some data, we generated hypothetical data in line with the real data. We used them to better understand the impact of selected suppliers on the three objectives' values and the trade-off between them, and to analyse the impact of parameters such as holding cost and penalty cost, supplier risks and the business strategy on the supplier selection and recommended order quantities and times of ordering. We assumed that all three objectives have the same weights, 1/3. In all the experiments reported below, AIMMS found optimal solutions. Data used in the experiments include 6 suppliers and 10 components. They are given in Tables 2 to 4. Fuzzy lead times and fuzzy non-conformance rates were generated based on the available historical data and in consultation with the company expert.

Table 2 Trapezoidal fuzzy numbers representing lead times and non-conformance rates of suppliers

Supplier	Component	Fuzzy lead time				Fuzzy non-conformance rate			
I	c	l_1	l_2	l_3	l_4	q_1	q_2	q_3	q_4
1	1	10	11	13	14	0	0.05	0.15	0.20
	3	6	7	9	10	0	0.05	0.15	0.20
	5	16	17	19	20	0	0.05	0.15	0.20
	7	14	16	18	19	0.05	0.15	0.20	0.25
	9	6	7	9	10	0	0.05	0.15	0.20
2	2	17	19	21	22	0.05	0.15	0.20	0.25
	4	12	13	15	16	0	0.05	0.15	0.20
	6	14	15	17	18	0	0.05	0.15	0.20
	8	16	17	19	20	0	0.05	0.15	0.20
	10	14	16	18	19	0.05	0.15	0.20	0.25
3	1	10	11	13	14	0	0.05	0.15	0.20
	3	8	9	11	12	0	0.05	0.15	0.20
	5	16	17	19	20	0	0.05	0.15	0.20
	7	13	15	17	18	0.05	0.15	0.20	0.25
	9	6	7	9	10	0	0.05	0.15	0.20
4	1	10	13	16	18	0.15	0.25	0.30	0.35
	5	16	19	22	24	0.15	0.25	0.30	0.35
	6	13	16	19	21	0.15	0.25	0.30	0.35

5	2	15	18	21	23	0.15	0.25	0.30	0.35
	3	7	9	11	12	0.05	0.15	0.20	0.25
	9	5	7	9	10	0.05	0.15	0.20	0.25
	10	13	16	19	21	0.15	0.25	0.30	0.35
6	2	13	15	17	18	0.05	0.15	0.20	0.25
	5	16	17	19	20	0	0.05	0.15	0.20
	8	16	17	19	20	0	0.05	0.15	0.20
	9	6	8	10	11	0.05	0.15	0.20	0.25

Table 3 Input data for components included in the BOM

Supplier	Component	Component availability	Unit purchase cost	Fine for early/late delivery	Fine for non-conformance
I	C	β_c^i	m_c^i	ft_c^i	fq_c^i
1	1	1	4.0	0.10	4.0
	3	1	1.2	0.03	1.2
	5	1	16.0	0.40	16.0
	7	1	2.2	0.06	2.2
	9	1	30.0	0.75	30.0
2	2	1	100.0	2.50	100.0
	4	1	20.0	0.50	20.0
	8	1	20.0	0.50	20.0
	10	1	54.0	1.35	54.0
3	1	1	4.5	0.11	4.5
	3	1	2.0	0.05	2.0
	5	1	18.0	0.45	18.0
	7	1	2.8	0.07	2.8
	9	1	34.0	0.85	34.0
4	1	1	4.4	0.11	4.4
	5	1	17.0	0.43	17.0
	6	1	68.0	1.70	68.0
5	2	1	130.0	3.25	130.0
	3	1	1.5	0.04	1.5
	9	1	32.0	0.80	32.0
	10	1	56.0	1.40	56.0
6	2	1	200.0	5.00	200.0
	5	1	20.0	0.50	20.0
	8	1	22.0	0.55	22.0
	9	1	31.0	0.78	31.0

Table 4 BOM and holding cost of all components

Component	C	1	2	3	4	5	6	7	8	9	10
BOM	B_c	50	6	0	100	33	0	15	24	0	8
Unit holding cost	h_c	0.4	5	1.5	2	1.8	4.6	0.3	0.2	0.4	0.6

Finally,

- status of supplier 1 is E, supplier 2 is G, supplier 3 is G, supplier 4 is M, supplier 5 is N, supplier 6 is M.
- $rs^1 = 14, rs^2 = 38, rs^3 = 25, rs^4 = 70, rs^5 = 50, rs^6 = 45.$
- $rp_1 = 18,\ \ rp_2 = 76,\ rp_3 = 50,\ rp_4 = 35,\ rp_5 = 20,\ rp_6 = 31,\ rp_7 = 80,$ $rp_8 = 11, rp_9 = 44, rp_{10} = 60.$
- $b_c^i = 1, i = 1, \dots, 6,\ c = 1, \dots, 10.$
- $f = 5000$
- $T = 24$
- $a = 4.$

Trade-off between objective functions' values

In order to analyse a trade-off to be made between objective functions' values, we first found the optimal set of suppliers for the required components, the optimal quantity to be ordered for each component and the optimal time of ordering using the data given in the previous section (Table 5). Then, we randomly selected another 14 alternative sets of suppliers and sorted them in the ascending order with respect to the cost incurred, as given in Table 6. Please note that the optimal set of suppliers is alternative 2. In each alternative, we assume that each component is supplied by one supplier only, i.e., the order is not split among different suppliers, and the quantities and the times of ordering are the same as in the optimal solution.

Table 5 Optimal set of suppliers, quantities to be ordered and times of ordering

Component	Supplier	Quantity	Time of ordering (in weeks)
1	3	63	6
2	6	8	0
4	2	125	4
5	3	42	0
7	3	20	2
8	2	30	0
10	2	11	0

Table 6 Alternative sets of suppliers

		Supplier						
		Component 1	Component 2	Component 4	Component 5	Component 7	Component 8	Component 10
Alternative	1	3	6	2	1	3	2	2
	2	3	6	2	3	3	2	2
	3	1	6	2	1	1	6	5
	4	1	6	2	6	3	6	5
	5	1	6	2	6	3	6	5
	6	3	2	2	6	1	2	2
	7	3	2	2	6	3	2	2
	8	3	2	2	6	1	6	5
	9	3	2	2	6	1	6	2
	10	1	5	2	1	1	6	5
	11	3	5	2	6	3	2	5
	12	3	5	2	3	3	2	2
	13	4	2	2	4	1	6	2
	14	4	6	2	3	3	2	2
	15	4	2	2	4	1	2	5

The normalised objective functions' values achieved for the 15 alternatives of suppliers' selection are presented in Figure 5. One can notice that the three objectives are not correlated and the trade-off between them has to be found. For example, the normalised cost value (Objective 1) incurred in alternative 4 (Objective 2) is smaller than in alternative 5 (0.199 and 0.295, respectively), while the normalised risk value for alternative 4 is higher than for alternative 5 (0.295 and 0.143, respectively). This means that while alternative 4 is better cost-wise compared to alternative 5, the selected suppliers in alternative 4 are more risky than in alternative 5. Similarly, while the normalised cost values in alternatives 4 and 5 are increased (from 0.199 to 0.295, respectively), achievement of the business strategy (Objective 3) is better in alternative

5 than in alternative 4, i.e., the normalised achievement penalty is decreased from 0.100 in alternative 4 to 0.000 in alternative 5, when all the selected suppliers have G status and the business strategy is fully achieved. Also, for example, suppliers in alternative 12 have a higher normalised risk compared to suppliers in alternative 13, (0.190 and 0.167, respectively), but are better with respect to achieving business strategy (normalised penalties are 0.006 and 0.094, respectively).

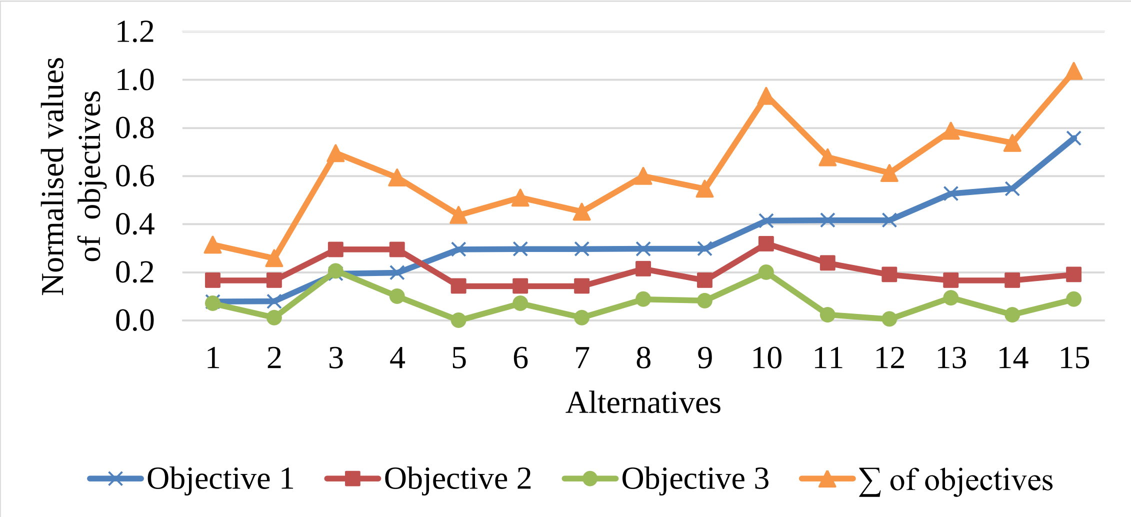

Figure 5 Normalised objective functions' values for 15 alternative sets of suppliers

One can conclude that the three objectives which are used to evaluate suppliers from different aspects can be in conflict. For example, selecting certain suppliers can be more expensive, but less risky and vice versa. Also, while certain suppliers can be more expensive, their selection can lead to a higher business strategy achievement. Finally, there are suppliers that are less risky, but less in line with the business strategy. Therefore, the problem is considered as a multi-objective problem, with the aim to find a trade-off between these objectives.

Analysis of the impact of fuzzy non-conformance rate

Fuzzy non-conformance rate of each supplier is varied, from the values given in Table 2, to increases of 10%, 25% and 50%, where all values (q_1, q_2, g_3, q_4) which define the fuzzy non-conformance rates are increased by 10%, 25% and 50%, respectively, as presented in Table 7.

Table 7 Varied fuzzy non-conformance rates

Component	Supplier	Non-conformance rate			
c	*i*	Initial	Increased by 10%	Increased by 25%	Increased by 50%
1	1	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	3	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	4	(0.15,0,25,0.30,0.35)	(0.136,0.227,0.333,0.389)	(0.120,0.2,0.4,0.467)	(0.100,0.167,0.6,0.7)
2	2	(0.05,0.15,0.20,0,25)	(0.045,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
	5	(0.05,0.15,0.20,0,25)	(0.045,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
	6	(0.05,0.15,0.20,0.25)	(0.045,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
3	1	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	3	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	5	(0.05,0.15,0.20,0.25)	(0.045,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
4	2	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
5	1	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	3	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	4	(0.15,0,25,0.30,0.35)	(0.136,0.227,0.333,0.389)	(0.120,0.2,0.4,0.467)	(0.1,0.167,0.6,0.7)
	6	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4,)
6	4	(0.15,0,25,0.30,0.35)	(0.14,0.227,0.333,0.389)	(0.120,0.2,0.4,0.467)	(0.1,0.167,0.6,0.7)
7	1	(0.05,0.15,0.20,0,25)	(0.045,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
	3	(0.05,0.15,0.20,0,25)	(0.05,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
8	2	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	6	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
9	1	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	3	(0,0.05,0.15,0.20)	(0,0.045,0.167,0.222)	(0,0.04,0.2,0.267)	(0,0.033,0.3,0.4)
	5	(0.05,0.15,0.20,0.25)	(0.045,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
	6	(0.05,0.15,0.20,0.25)	(0.045,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
10	2	(0.05,0.15,0.20,0,25)	(0.045,0.136,0.222,0.278)	(0.040,0.12,0.267,0.333)	(0.033,0.1,0.4,0.5)
	5	(0.15,0.25,0.30,0.35)	(0.136,0.227,0.333,0.389)	(0.120,0.2,0.4,0.467)	(0.1,0.167,0.6,0.7)

To mitigate the risk of receiving non-conformed components, more components are ordered than required by the BOM, i.e., the required number of each component *c*. The higher the non-conformance rate, the higher the order. Increases in the orders are given in the brackets, in Table 8. However, this relation is not linear and depends on many other parameters as discussed below.

Table 8 Order quantities when the non-conformance rates are increased

Component	Bill of Material	Supplier	Non-conformance rate			
c	B_c	i	Initial $\tilde{Q}_c^i$	Increased by 10%	Increased by 25%	Increased by 50%
1	50	1	0	0	0	0
		3	63	82 (+30%)	82 (+30%)	83 (+32%)
		4	0	0	0	0
2	6	2	0	0	0	0
		5	0	0	0	0
		6	8	9 (+13%)	11 (+38%)	12 (+50%)
4	100	2	125	129 (+3%)	137 (+10%)	167 (+34%)
5	33	1	0	0	0	0
		3	42	43 (+2%)	50 (+19%)	55 (+31%)
		4	0	0	0	0
		6	0	0	0	10 (+0.24%)
7	15	1	0	0	0	0
		3	20	21 (+5%)	25 (+25%)	30 (+50%)
8	24	2	30	31 (+3%)	33 (+10%)	40 (+33%)
		6	0	0	0	0
10	8	2	11	12 (+9%)	15 (+36%)	16 (+45%)
		5	0	0	0	0

It is interesting to notice that the same suppliers are selected for all 4 different non-conformance rates for all 7 components; for example, supplier 3 is selected to supply component 1 for all different non-conformance rates. This is expected as all non-conformance rates of all suppliers are increased by the same percentage. However, it is recommended to use a dual sourcing for component 5 when non-conformance is increased by 50%, i.e., to use suppliers 3 and 6. Both suppliers have better delivery performance with respect to non-conformance rate and lead time, and have to pay higher fines for non-conformance compared to other eligible suppliers, namely suppliers 1 and 4. In addition, both suppliers are selected as they have similar characteristics; still more quantity is recommended to be ordered from supplier 3 which has slightly lower unit purchase cost and pays slightly lower fine to the manufacturer compared to supplier 6. Furthermore, it has the G status, while supplier 6 has the M status.

However, if non-conformance rate of only one supplier is increased, it can have an impact on the supplier selection. For example, if only the non-conformance rate of supplier 3 for component 1 is increased by 50%, supplier 1 is selected instead of supplier 3 (see Table 9). Although supplier 1 has the E status which does not contribute to business strategy achievement, while supplier 3 has the preferred G status, supplier 1 has a cheaper unit purchase cost than supplier 3 (4 compared to 4.5) and a lower risk (14 compared to 25). Furthermore, in this case, the order quantity from supplier 1 is decreased from 83 to 75, because supplier 1 has the smaller non-conformance rate than the increased non-conformance rate of supplier 3; (0, 0.05., 0.15, 0.20) compared to (0, 0.033, 0.3, 0.4). One can notice that supplier 4 is not selected instead of supplier 3, because it has a longer lead time, and higher *risk_score* than supplier 3 and non-conformance rate similar to the increased non-conformance rate of supplier 3. This demonstrates that the model makes a trade-off between all three objectives.

Table 9 Increase of non-conformance rate of supplier 3 only

Component	Bill of Material	Supplier	Non-conformance rate	
c	B_c	i	Initial $\tilde{Q}_c^i$	Increased by 50%
1	50	1	0	75 (+19%)
		3	63	0
		4	0	0

Analysis of the impact of unit holding cost

In order to analyse the impact of unit holding cost on both order quantity and time of ordering, the unit holding is changed from the initial value (100%), which the manufacturer currently takes into account, to a reduction of unit holding cost of 50%, and increases to 200% and 400%. It is observed that the ordering quantities $x_c^i, c = 1, \dots, 10, i = 1, \dots, 6$, remain the same (Table 10). The model recommends the minimum quantities to be ordered, otherwise, ordering higher quantities, would increase the total cost, due to the higher holding costs. However, varying the unit holding costs, h_c^i, has an impact on the time of ordering, as illustrated in Figure 6.

Table 10 Ordering quantity and supplier selection for different values of h_c

		Component c						
		1	2	4	5	7	8	10
h_c	50%	63	8	125	42	20	30	11
	100%	63	8	125	42	20	30	11
	200%	63	8	125	42	20	30	11
	400%	63	8	125	42	20	30	11
Ordered from supplier		3	6	2	3	3	2	2

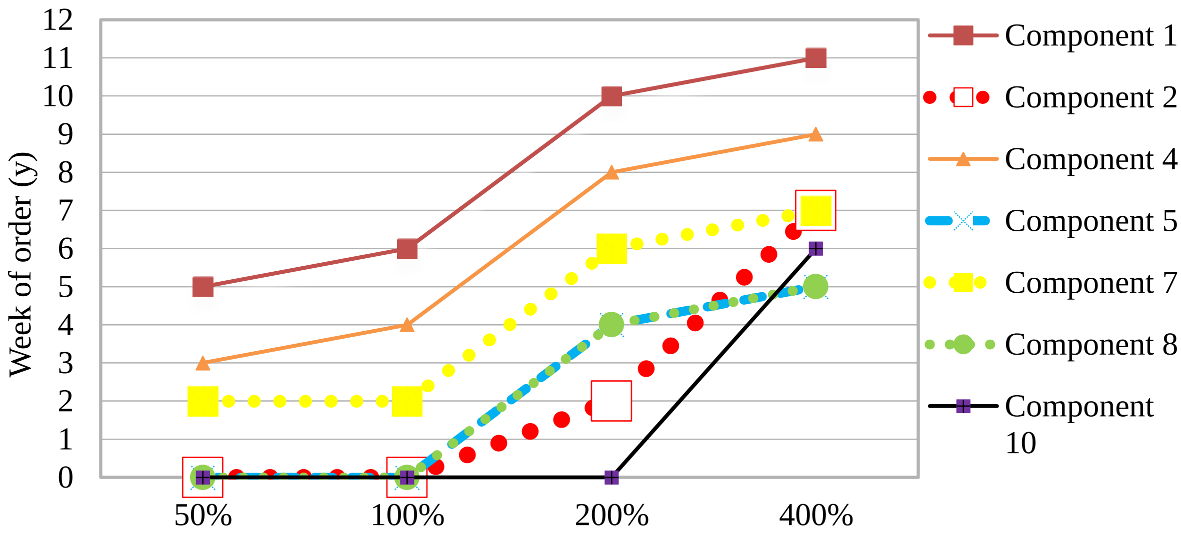

Figure 6 Time of ordering of components with different unit holding costs

One can see when the unit holding cost is increasing, the ordering is recommended later; for example, when the unit holding costs of both components 1 and 4 are increased to 400% of the initial unit holding cost values, the ordering is recommended 6 weeks later (in week 11 and 9, respectively) compared to the case when unit holding cost is 50% of the initial holding cost (in week 5 and 3, respectively). However, late ordering does not necessarily incur the lower total cost. The holding cost is balanced with other costs, such as the fine that the manufacturer must pay in the case of late delivery, number of components needed and the lead times. For example, the unit holding cost of component 8 is much smaller than the unit holding cost of component 4, (0.2 and 2, respectively) and more component 4 is required than component 8, (100 and 24, respectively) as given in Table 4. Therefore, it is recommended to order component 8 earlier than component 4, for all 4 cases of the unit holding costs. On the other hand, the unit holding cost of component 5 is smaller compared to component 2 (1.8 and 5, respectively) that suggests that component 5 could be ordered earlier. However, when holding cost is increased to 200%, the model recommends ordering of component 5 later than component 2, even though its lead time is higher, (16, 17, 19, 20) and (13, 15, 17, 18), respectively. Once the holding cost is increased to 400%, it is recommended to order component 5 earlier than component 2, as the holding cost of component 2 becomes too high and the longer lead time of component 5 has a dominant role. This analysis demonstrates that increasing the unit holding cost leads to later ordering. However, it can generate either an increased or decreased cost of handling a component depending on other parameters, as mentioned above.

Analysis of the impact of supplier's risks

In this experiment, a trade-off between the cost and the risk is analysed, while it is assumed that all suppliers of each component have the same statuses, i.e., contribute equally to the business strategy achievement. Table 11 presents data of 4 different components considered in this experiment, where each component is supplied by suppliers with the same statuses, but have different risks. Their *risk_scores* are varied in Case 1, Case 2 and Case 3. The remaining data are the same as given previously. Table 12 shows selected suppliers, quantities and times of orders in the three cases.

Table 11 Statuses and *risk_scores* of suppliers

Component	Supplier	Supplier status	$risk\_score_c^i$		
c	i	φ^i	Case 1	Case 2	Case 3
1	1	N	25	25	50
	3	N	25	50	50
	4	N	25	25	25
2	2	M	30	50	50
	5	M	30	29	50
	6	M	30	30	25
5	1	G	25	40	50
	3	G	25	30	70
	4	G	25	50	25
	6	G	25	25	26
8	2	E	70	70	50
	6	E	70	50	70

Table 12 Selected suppliers, order quantities and times of orders

c	Case 1			Case 2			Case 3		
	Selected supplier i	x_c^i	y_c^i	Selected supplier i	x_c^i	y_c^i	Selected supplier i	x_c^i	y_c^i
1	3	63	6	1	63	2	4	63	10
2	2	8	3	6	8	0	6	8	0
5	1	21	0	6	42	0	4	21	0
	3	21	0	-	-	-	6	21	0
8	2	30	0	6	30	0	2	30	0

As it can be seen in Table 12, suppliers' risks influence the supplier selection, but a trade-off with the cost has to be made. Furthermore, quantities of orders remain the same regardless to the suppliers' *risk_scores*. Three suppliers can supply component 1, namely suppliers 1, 3 and 4. However, supplier 4 has a longer lead time and higher non-conformance compared to suppliers 1 and 3. Therefore, in Case 1, when all the three suppliers of component 1 have the same *risk_score*, the model recommends supplier 3. However, when *risk_score* of supplier 3 is increased in Case 2 and Case 3, to 50, the model changes the recommendations to suppliers with the smaller *risk_scores*, namely 1 and 4, respectively. It might be interesting to notice that in Case 3, supplier 4 is selected because of its lowest risk, although it has worse lead time and non-conformance rate compared to suppliers 1 and 3. Also, the ordering times changes depending on suppliers selected. Three suppliers, 2, 5 and 6 are considered to supply component 2. Supplier 2 has the highest lead time, and supplier 6 has the highest non-conformance rate. All three suppliers generate similar costs, and, therefore, in each case, the supplier risk has the dominant role in selecting the supplier. Therefore, the supplier with the smallest risk, i.e., supplier 2, supplier 5 and supplier 6 in Case 1, Case 2 and Case 3, respectively, are selected. The selection of suppliers for component 5, changes in each of the three cases. Supplier 4 has the highest lead time, while suppliers 1, 3 and 6 have the same lead times and supplier 4 has the highest non-conformance rate, while suppliers 1, 3 and 6 have the same non-conformance rate. Dual sourcing is recommended in Case 1 and in Case 3. However, the two suppliers with the lowest *risk_scores* are always recommended, i.e, suppliers 1 and 3 and 4 and 6 in Case 1 and Case 3, respectively. As previously, although supplier 4 has the longest lead time and the highest non-conformance rate which generate high cost, it is selected in Case 3, because it has the lowest *risk_score*. Two suppliers of component 8, namely supplier 2 and 6, have the same lead times and non-conformance rates, and similar fines to pay in the case of early/late delivery and non-conformance. That is why in Cases 2 and 3, when suppliers 2 and 6 have different *risk_scores,* the model selects the supplier with the lower risk, i.e., supplier 6 and supplier 2 in Case 2 and Case 3, respectively.

Analysis of the impact of the business strategy achievement and suppliers' statuses

In this experiment, we are focused on component 5 only and the corresponding suppliers, 1, 3, 4, and 6, with different statuses and different risks. The input data for the three cases are given in Tables 2, 3 and 13, while the results are given in Table 14. Supplier 4 has the worst lead time and non-conformance rate. In Case 1 and Case 2, the model selects dual-sourcing from the two suppliers, 1 and 3, with the same G status and the same *risk_scores*. It is ordering more than it is required in the BOM; 33 components are required, while 42 components are ordered in total from suppliers 1 and 3 (42=21+21). In Case 2, the model still recommends dual-sourcing from these suppliers, although supplier 3 has higher *risk_score* than in Case 1. However, in Case 3, where risk of supplier 3 is very high, the model does not recommend dual-sourcing anymore. When the risk of supplier 3 increases to 80, the model selects to order 42 components from supplier 1 only, which has the best category G and the lowest *risk_score* 25.

Table 13 Input data for suppliers with different statuses and with different $risk\_score$

Component	Supplier	Supplier status	$risk\_score_c^i$		
c	i	φ^i	Case 1	Case 2	Case 3
5	1	G	25	25	25
	3	G	25	50	80
	4	M	50	25	25
	6	M	60	50	50

Table 14 Selected suppliers, order quantities and times of orders

c	Case 1			Case 2			Case 3		
	Selected supplier i	x_c^i	y_c^i	Selected supplier i	x_c^i	y_c^i	Selected supplier i	x_c^i	y_c^i
5	1	21	0	1	21	0	1	42	0
	3	21	0	3	21	0	-	-	-

Analysis of the impact of problem size on the computation time

In this experiment, the size of the problem is increasing by increasing the number of suppliers i and the number of components c. The computational time is presented in Table 15. The computation time is increasing in a non-linear manner. The optimum solutions are found for problems up to 30 suppliers and 80 components.

Table 15 Computation time

Size of the problem	i = 6 c = 10	i = 15 c = 40	i = 40 c = 60	i = 30 c = 80
Computation time	22min 35s	1h 29min	7h 12min	11h 51min

Conclusions and directions for further research

A multi-objective optimisation model is developed to select suppliers and to determine how much and when to order in a real-world supply network, considering three objectives: minimisation of cost, minimisation of risk and maximisation of business strategy achievement. Different types of uncertainties are considered. First, uncertain data about lead times and non-conformance rates of delivered components are specified using imprecise terms and are modelled using fuzzy numbers. Vague knowledge of categorising suppliers based on components and suppliers' risks is modelled using fuzzy If-Then rules. They are handled using a modified Takagi and Sugeno method of fuzzy logic and incorporated in the multi-objective model. The model is subsequently transformed into a crisp, single objective optimisation model which is implemented in AIMMS.

Various experiments are carried out to gain better understanding of SN performance in the presence of uncertainty and three objectives under consideration. It is shown that the three objectives behave differently, i.e., certain suppliers can lead to lower cost, but can be more risky and less in line with the business strategy, and vice versa. Also, suppliers can have lower risk, but can contribute less to the business strategy achievement, and vice versa. It is confirmed than increases in uncertain non-conformance rate cause increases in quantities to be ordered in a non-linear manner. Furthermore, an increase in a unit holding cost of a component has to be balanced with other costs. It leads to later ordering, but can generate either higher or lower cost of handling a component depending on other parameters including the fine the manufacturer has to pay in case of the late delivery, number of components needed and lead times. Suppliers' risks and statuses, including G-Grow, E-Exit, M-Maintain, N-New, have an impact of the supplier selection and have to be in balance with the SN cost.

Finally, it is concluded that the model proposed can be applied to a large SN. The optimal solution can be found for SNs with up to 30 suppliers and 80 components.

Further research will be carried out to extend the model to include annual demand for multiple engines and to compare the performance of the SN optimised using the proposed model with the performance achieved in practise.

Appendix. Fuzzy arithmetics

Fuzzy arithmetic operations are used in calculating the total cost in Objective 1 as given in Table 16.

Table 16 Fuzzy operators where $\tilde{L}$ and $\tilde{Q}$ are trapezoidal fuzzy numbers $\tilde{L} = (l_1, l_2, l_3, l_4)$ and $\tilde{Q} = (q_1, q_2, q_3, q_4)$

Operator	Syntax	Formula
Addition	$\tilde{L} + \tilde{Q}$	$(l_1 + q_1, \quad l_2 + q_2, \quad l_3 + q_3, \quad l_4 + q_4)$
Subtraction	$\tilde{L} - \tilde{Q}$	$(l_1 - q_4, \quad l_2 - q_3, \quad l_3 - q_2, \quad l_4 - q_1)$
Multiplication	$\tilde{L} \times \tilde{Q}$	$(l_1 \times q_1, \quad l_2 \times q_2, \quad l_3 \times q_3, \quad l_4 \times q_4)$
Multiplication with scalar *r*	$r \times \tilde{L}$	$(l_1 \times r, \quad l_2 \times r, \quad l_3 \times r, \quad l_4 \times r)$
Division	$\tilde{L} \div \tilde{Q}$	$(l_1 \div q_4, \quad l_2 \div q_3, \quad l_3 \div q_2, \quad l_4 \div q_1)$
Maximum between fuzzy value and scalar *r*	max $(\tilde{L}, r)$	$(\max(l_1, r), \max(l_2, r), \max(l_3, r), \max(l_4, r))$
Maximum between two fuzzy values	max $(\tilde{L}, \tilde{Q})$	$(\max(l_1, q_1), \max(l_2, q_2), \max(l_3, q_3), \max(l_4, q_4))$
Relation ≤ between scalar r and fuzzy value	$r \leq \tilde{L}$	$r \leq l_1$
Defuzzification	$Defuzz(\tilde{L}_c^i)$	$\dfrac{l_1 + 2 \times l_2 + 2 \times l_3 + l_4}{6}$

Once the fuzzy total cost is calculated in Objective 1, it is defuzzified using the defuzzified method given in Table 16. The defuzzification operation determines a scalar value that represents most appropriately the fuzzy number under consideration.

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