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A fuzzy scenario-based optimisation of supply network cost, robustness and shortages

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ABSTRACT

Supply network (SN) robustness has become an important issue in SN management. In this paper, we refer to SN as robust, if it maintains its performance in the presence of uncertainty in SN parameters, namely uncertain changes in customer demand. A customer forecasts its demand in terms of requested quantity and time of delivery. This forecasted demand can be changed until a certain time. After that, the customer is committed to its demand. However, a manufacturer has to order materials in advance to produce its product without knowing the exact changes in customer demand. The materials can be ordered either from a standard supplier, or, from an emergency supplier, if there is not enough material in stock and/or there is not enough time for a delivery from the standard supplier. We define a new concept of fuzzy scenarios that comprise uncertain changes in customer demand. These changes are specified by linguistic terms and modelled using fuzzy numbers. The robustness of an SN is measured in a novel way as the variance of costs incurred in all fuzzy scenarios. This means that the robust SN maintains its cost in the presence of uncertain changes in customer demand. A novel fuzzy multi-objective optimisation model is developed, which determines quantities of materials to be ordered by a manufacturer from a standard supplier and times of ordering. The objectives considered simultaneously embed all fuzzy scenarios and include the minimisation of total SN cost, the maximisation of robustness and the minimisation of shortages. Various experiments are carried out to analyse the relationship between SN parameters and SN performance. Results obtained by applying the SN model demonstrate that robustness can be increased and shortages can be decreased, but, as expected, at a higher SN cost. In the case of the high ratio of the unit purchase cost from the emergency supplier to the unit surplus cost, a considerable increase of robustness and a decrease of shortages can be achieved. Finally, it is shown that the model can be applied to large-scale SNs.

1. Introduction

In today's global supply networks (SNs) identifying, understanding and managing various types and sources of uncertainty that can affect SNs have become very important. Traditional supply chains (SCs) emphasise the linear flow of products from suppliers to customers, while SNs focus on the web of connections. Still, these two terms are used interchangeably in the literature. In this paper, in line with the problem under consideration, we are going to use the term SN. Different concepts have been introduced to address SN behaviour and performance in the presence of uncertainty. One of them often used in the SN context is robustness (Monostori, 2018).

Generally, an SN is considered to be robust if it has consistent performance in an uncertain environment with very little variation in its output (Christopher & Rutherford, 2004). Robust optimisation provides good and stable solutions when dealing with uncertain parameters (Bertsimas & Thiele, 2004). Mulvey et al. (1995) classifiedrobust optimisation based on two concepts, solution robust and model robust. A solution was defined as robust if it remained "close" to the optimal solution for all values of uncertain input data, and a model was robust if it remained "almost" feasible for all values of uncertain data. Uncertainty in SN optimisation has often been treated using a scenario-based optimisation method and concepts of probability theory. Each scenario is typically represented by uncertain SN parameters and their realisation. The scenario is assigned a corresponding probability of its occurrence. Scenarios have been developed to represent various SN uncertainties including: SN hazards (Klibi & Martel, 2012), suppliers' disruptions (Gaonkar & Viswanadham, 2007), future economic states (Rahmani

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et al., 2013), uncertain future demand/return of products (Kaya et al., 2014) or social-distancing status during the Covid-19 pandemic (Perdana et al., 2020). However, in the real world, it is not always possible to specify a probability distribution of uncertain parameters.

The development of our model is motivated by a real world manufacturer's problem; however, as many companies face similar issues, the model has been constructed to be generic. The problem is that the customer forecasts its demand with respect to both quantity and time when the quantity is required and can alter its demand until a certain time, when the demand becomes fixed and can no longer be changed. The manufacturer has to order materials to produce its product without knowing the exact quantities and times that will be required. The manufacturer has to determine how many materials to order, and when, from a standard supplier in such a way as to be able to fully satisfy a fixed customer demand. Holding higher quantities of materials in stock increases the SN cost and materials can even become obsolete. However, if there is not enough material ordered from the standard supplier and/or there is not enough time for a delivery from the standard supplier, the materials have to be ordered from a more expensive emergency supplier with a shorter lead time. In order to try to address the manufacturer's problem, we introduce a new concept of fuzzy scenarios that comprise descriptions of changes in both demanded quantity and time of delivery. These changes in forecasted customer demand are specified in our research using linguistic terms, such as "*more* quantity than forecasted", "at *earlier time* of delivery than forecasted", etc. This approach can be very convenient to use in practice.

We develop a novel multi-objective SN optimisation model, which minimises the total SN cost, maximises SN robustness, i.e., variations of costs incurred in all fuzzy scenarios, and minimises the shortages of materials in the presence of changes in customer demand. We consider the SN to be robust, if it maintains its cost in the presence of uncertainty in changes in customer demand. The fuzzy scenarios are embedded in the objectives. Various experiments are carried out which provide an insight into a trade-off between SN cost, robustness and shortages in the presence of fuzzy changes in customer demand. The impact of different probabilities of these fuzzy changes on SN performance is investigated. The model's computational requirements are analysed as well.

The novelties proposed in this research are as follows: (1) A new concept of fuzzy scenarios is defined to model uncertainty in changes in customer demand, where changes include both those of requested quantity and time. Instead of dealing with the crisp historical data of demand changes and their probabilities, we define scenarios of demand changes using imprecise linguistic terms, which makes the approach more applicable in practice. To the best of our knowledge, scenario-based optimisation models developed so far have included crisp historical data with corresponding probabilities only and not linguistic terms. (2) A new measure of SN robustness is proposed as the variance of costs incurred in all fuzzy scenarios. (3) Experiments carried out bring useful managerial insights into SN performances, including cost, robustness and shortages, and a link/trade-off between them. The impact of different SN parameters and scenario probabilities on SN performance and order decisions are analysed.

The rest of the paper is organised as follows. The literature review is presented in Section 2. Section 3 contains the problem statement, while Section 4 describes a fuzzy scenario-based multi-objective optimisation model for the real-world SN. Section 5 provides the results and their analysis, and Section 6 outlines some practical and managerial insights obtained. Section 7 presents the conclusion and directions for future work.

2. Literature review

Various optimisation models for SNs have been developed in recent years. The literature review is focused on three approaches to optimisation that consider uncertainty and are relevant to this research: robust SN optimisation, scenario-based SN optimisation and fuzzy SN optimisation.

A robust SN optimisation approach which has included both model robustness (almost feasible) and solution robustness (near to optimality) has been widely used. Different models for finding a trade-off between solution robustness and model robustness have been developed. For example, in the area of aggregate production planning (APP), Leung and Wu (2004) considered an uncertain manufacturing environment and proposed a robust optimisation model to minimise the total production cost. Mirzapour Al-e-hashem et al. (2011) developed a robust, multi-objective, mixed-integer, non-linear programming model. The objectives were to minimise the total SN cost and to maximise the customer's satisfaction level by minimising shortages, in such a way as to fulfil the product demand. Two objective functions were defined, where the first objective represented solution robustness, capturing the firm's desire for low costs and its degree of risk aversion, while the second objective represented model robustness, penalising solutions that failed to meet demand in a scenario or violated constraints such as capacity.

Some researchers have mainly concentrated on solution robustness. For example, Leung et al. (2007) investigated a production planning problem for perishable products and provided a robust solution for coping with different economic environments, with respect to cost minimisation, including setup, production and labour costs. Kazemi Zanjani et al. (2010) addressed a multi-period, multi-product sawmill production planning problem under uncertainties in the quality of raw materials. A robust production plan was proposed regarding the minimisation of backorder size (i.e., service level) variability. Two robust optimisation models were proposed with a different variability of customer service level. A trade-off between the expected backorder/inventory cost and the decision-maker risk-aversion level was considered. Alem and Morabito (2012) applied robust optimisation for lot-sizing and cutting stock for a furniture production planning. The authors found out that solution robustness could be achieved with a small probability of constraint violation, when there were uncertainties in the objective function coefficients only. Lim (2013) obtained a robust plan for the optimal bundle of price and order quantity for the retailer under uncertainties in demand and purchase costs. The author analysed the robustness of this solution by comparing it with deterministic case solutions in terms of the gains and losses in different uncertain settings. More recently, Fazli-Khalaf et al. (2019) considered laboratories and hospitals in a blood SN. Two methods were proposed to find robust and risk-averse solutions related to transportation decisions, when facing emergency situations.

The scenario-based approach has typically been used to model uncertainty in parameters, where various realisations of parameters with associated probabilities have formed scenarios. For example, Pan and Nagi (2010) used scenarios to represent a collection of demands over time periods. The authors developed an optimisation model for an SN design in which the objective function included the weighted sum of solution robustness and model robustness. Rahmani et al. (2013) modelled all the uncertainties, including customer demand, production, inventory and subcontracting costs, in scenarios. They presented a robust mixed-integer programming optimisation model to determine a robust production plan for a multi-period, multi-product, multi-machine, two-stage production system. It was concluded that the proposed robust model was efficient in any system that required the minimisation of the total cost and low fluctuations when facing uncertainties. Baghalian et al. (2013) proposed a new stochastic mathematical formulation of a multi-product SN. Their work described supply uncertainty through scenarios and presented demand uncertainty as a random variable with a known disruption function. Kaya et al. (2014) formed scenarios to handle uncertainties in demand and returns of parts and products. They developed both a two-stage stochastic optimisation model and a robust optimisation model for capacity planning, and production and inventory decisions in a closed-loop manufacturing system for modular products. Salehi et al. (2017) applied such an approach to a blood SN design for dealing with a natural disaster, and proposed a robust two-stage, multi-period stochastic model. They generated scenarios for the demand of blood units of different types and their derivatives. Scenarios have also been used to describe disruptions, as in Jabbarzadeh et al. (2018). The authors modelled a closed-loop SC under the risk of disruption, using a stochastic, robust optimisation approach to determine facility locations and lateral transshipment quantities that minimised the total SC cost.

Apart from using probability distributions and scenarios to model uncertain parameters in SNs, an alternative approach based on fuzzy sets has been investigated. Uncertainty in SN parameters has been modelled using imprecise linguistic terms which are specified based on managerial experience and judgement (e.g., Niknejad & Petrovic, 2017). Various fuzzy SN optimisation models have been developed. For example, Petrovic et al. (1999) proposed a fuzzy optimisation model for a serial SN with fuzzy demand and fuzzy supply. In addition, Liang (2008) developed a fuzzy model for integrated multi-product and multi-time period production/distribution planning with the fuzzy objectives of the minimisation of total cost and delivery time. Mahnam et al. (2009) developed a fuzzy model for an assembly SN in which the uncertainties in customer demand variability and in the reliability of external suppliers were modelled using linguistic terms. Fuzzy sets have also been used in modelling multi-objective optimisation problems. For example, Mohammed and Wang (2017) adopted the fuzzy optimisation approach to tackle a distribution planning problem for a food SN under multiple uncertainties in costs, demand and capacity levels of facilities, with multi fuzzy objectives such as the minimisation of transportation costs, CO2 emissions, the distribution time of products and the delivery rate. Mohammed et al. (2019) presented a fuzzy multi-objective programming model for SN design problems to determine the optimal number of facilities. The objectives included the minimisation of costs and environmental impacts and the maximisation of SC resilience. Mohammed (2019) developed an integrated fuzzy multi-objective approach for solving a two-stage supplier selection and order allocation problem in a meat SC, aiming to minimise the total costs, environmental impacts, travel time and, at the same time, to maximise social impact.

In the papers reviewed above, concepts of solution robustness, scenario-based modelling and fuzzy optimisation have been used separately. SN robustness has been handled as a crisp optimisation objective, while scenario-based modelling has used a crisp realisation of uncertain SN parameters. Fuzzy SN optimisation models have dealt with fuzzy objectives and/or fuzzy constraints. This paper presents a novel model which combines these concepts in the following way. Imprecise linguistic terms are used to describe uncertain changes in demand and to generate fuzzy scenarios. A fuzzy scenario comprises fuzzy values of changes in both demand quantity and demand delivery time. Our fuzzy optimisation model considers multi-objectives, including SN cost, robustness and shortages. The robustness objective is focused on maintaining the SN cost in the presence of fuzzy changes in customer demand. The model is based on a new measure of SN robustness which calculates the standard deviation of SN costs incurred in all fuzzy scenarios.

3. Problem statement

This research is motivated by a real-world SN problem faced by Malvern Tubular Components (MTC), UK. The company produces pipe and tubing assemblies and supplies various industries including energy, utilities, transportation and aerospace. However, the problem under consideration is relevant to manufacturers in general, in particular, those that are first-tier suppliers or are in “the middle of SNs”. In addressing this problem, we adopted the terminology used in MTC.

MTC supplies subsequent members of SN, who act as its customers. Its problem is to determine the quantity of materials to order from its suppliers, and when it should take place, in order to fully satisfy customer demand. A customer forecasts its demand in terms of quantity and time when it is required, at the beginning of a planning period. The planning period comprises the “forecast” and the “fixed” period. The customer is not committed to the order during the forecast period and may change demand before it becomes fixed, i.e., before the fixed period starts. Typically, the fixed period is up to two weeks before the time when demand quantity is required, because the manufacturer’s production time is two weeks. Therefore, in order to have the required materials (raw materials and components) ready and at a lower cost, the manufacturer has to purchase the materials in advance, before the demand becomes fixed. Materials are purchased from a number of standard suppliers. Each supplier has a different lead time and price. A supplier with a longer lead time offers a lower price. Generally, it is assumed that the suppliers’ capacity is sufficient to produce orders from the manufacturer and deliveries are on time. Therefore, suppliers’ delivery performance is not an issue.

Currently, the manufacturer applies a made-to-stock policy and uses a “buffer stock” of materials for production, to fulfil customer demand. Materials are purchased in advance from the standard suppliers. Before the demand becomes fixed, customers are able to change the demand quantity and/or required time. If there are not enough materials in stock and not enough time to restock using the standard suppliers, the manufacturer has to approach emergency suppliers. These companies have a lead time of up to two weeks, so can meet production needs, but are more costly. However, on the other hand, if the manufacturer buys too many materials in advance (from the standard suppliers), this causes a high surplus cost and might eventually lead to stock obsolescence and a high holding cost. It is, therefore, a complex task to determine the required stock as demand quantity and required time of delivery are uncertain.

We define fuzzy scenarios to capture uncertainty in changes in customer demand in terms of demand quantity and required time of delivery. In order to make the SN robust, its cost has to be maintained in the presence of uncertainty in changes in demand. The proposed model determines the quantity of materials to be ordered from the standard suppliers and the time of ordering in such a way as to minimise the SN cost, maximise SN robustness and minimise SN shortages. The decision what to order and when is to be made at the beginning of a planning period which starts when the customer places a forecasted demand for one type of product.

The following assumptions are made in line with the characteristics of the real-world problem under consideration:

- Customer demand must be satisfied.
- All suppliers are reliable in both quantity and time of delivery.
- Suppliers have sufficient capacities for providing ordered materials.
- The manufacturer has sufficient production capacity.
- Each order must be purchased from one supplier only, i.e., it cannot be split.

4. Fuzzy scenario-based multi-objective optimisation

The following notations are used:

Indexes

r	Materials $r = 1, \cdots, R$
s	Scenarios $s = 1, \cdots, S$

Decision variables

x_r	Quantity of material r to be ordered from the standard supplier in the planning period
y_r	The time to order material r from the standard supplier in the planning period

Table 1
Fuzzy scenarios which represent uncertainty in demand change.

Change in time $\widetilde{t}_s$	Change in quantity $\widetilde{q}_s$ *Less*	*About the same*	*More*
Earlier	Scenario 1	Scenario 2	Scenario 3
At about the same time	Scenario 4	Scenario 5	Scenario 6
Later	Scenario 7	Scenario 8	Scenario 9

Parameters

D	Forecasted demand quantity at the beginning of planning period
T	Forecasted demand time at the beginning of planning period
l_r	Lead time of the standard supplier for material r (in weeks)
m_r	Unit purchase cost of material r from the standard supplier
c_r	Unit purchase cost of material r from the emergency supplier ($c_r > m_r$)
θ_r	Quantity of material r required for the manufacturing of one product
π_r	Unit penalty cost for the surplus of material r
h_r	Holding cost of unit quantity of material r per unit time period (one week)
$\widetilde{q}_s$	Fuzzy change in demand quantity in scenario s
$\widetilde{t}_s$	Fuzzy change in demand time in scenario s (in weeks)
p_s	Probability of scenario s
v_i	Tolerance for achieving optimal objective's value or violating fuzzy constraint, where i refers to a fuzzy set in an objective or a constraint
V	Tolerance factor for all fuzzy objectives and fuzzy constraints

Other variables

φ_s^+	Surplus of materials purchased from the standard supplier in scenario s
φ_s^-	Shortage of materials purchased from the emergency supplier in scenario s
w_s	Total cost of scenario s
α	Degree of satisfaction with objectives' values achieved and constraints fulfilment.

4.1. Fuzzy scenarios

Uncertainty faced by the manufacturer is caused by changes that a customer can make in both quantity and time of forecasted demand. Typically, the company purchase manager will review the customer's previous demand and can specify that a certain customer, for example, usually orders *more* quantity than forecasted or requires a *similar* time of delivery as forecasted. We define a new concept of fuzzy scenarios to describe uncertainty when customer demand is for *Less*, *About the same* or *More* quantity, and it is required *Earlier*, *At about the same time* or *Later* than forecasted. There are nine fuzzy scenarios, where each scenario consists of two uncertain changes: change in quantity q_s and change in time t_s, as presented in Table 1. For example, Scenario 1 is "the requested quantity is *Less* than forecasted and it is requested *Earlier* than forecasted".

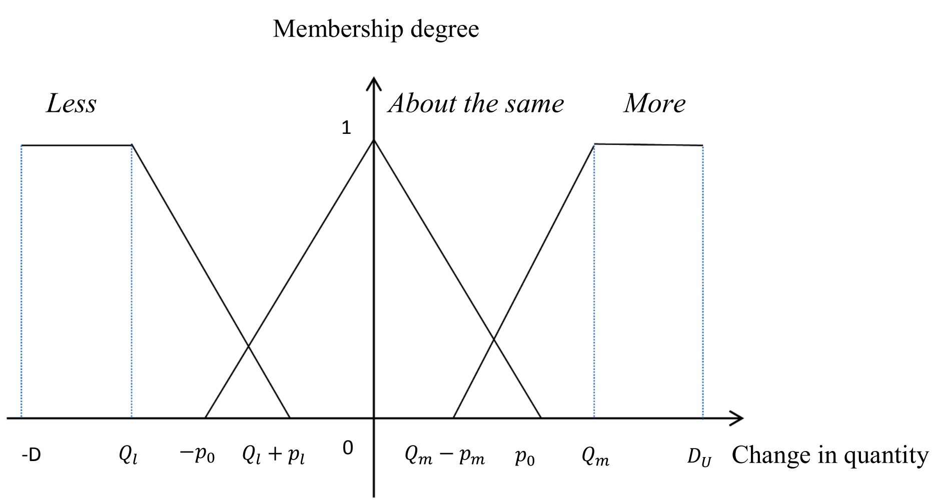

Fig. 1. Membership functions of change $\widetilde{q}_s$ in demand quantity.

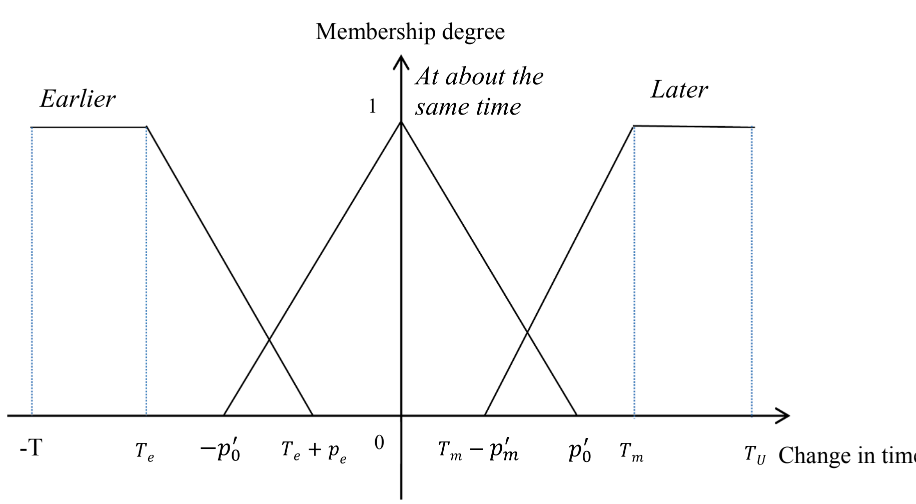

Fig. 2. Membership functions of change $\widetilde{t}_s$ in demand time.

Table 2
Costs incurred in scenarios.

Change in time $\tilde{t}_s$	Change in quantity $\tilde{q}_s$ Less	About the same	More
Earlier	Scenario 1: Shortage Surplus	Scenario 2: Shortage Surplus	Scenario 3: Shortage Surplus
At about the same time	Scenario 4: Surplus	Scenario 5: –	Scenario 6: Shortage
Later	Scenario 7: Holding Surplus	Scenario 8: Holding	Scenario 9: Holding Shortage

The linguistic terms are modelled using fuzzy sets. Change in demand quantity is described by three linguistic terms: *Less*, *About the same* and *More* which are modelled using fuzzy numbers presented in Fig. 1. The term *About the same* is modelled using a symmetric triangular fuzzy number which assumes changes $\pm p_0$. Terms *Less* and *More* are modelled using semi-trapezoidal fuzzy numbers. The minimum change can be *-D*, i.e., the demand is changed from D to 0. It is certainly *Less*, with degree of belief 1, if the change is between $-D$ and Q_l and it has decreasing degrees of belief that it is *Less* from Q_l to $Q_l + p_l$. Term *More* is defined in a similar way, where the maximum increase in demand can be D_u. Parameters Q_l, p_l, p_0, Q_m, p_m, and D_U are determined subjectively by the purchase manager.

The change in demand quantity is *Less*, i.e., the fixed order quantity is *Less* than the forecasted demand in scenarios $s = 1, 4, 7$ (as presented in Table 1). The membership function is defined as:

$$\mu_{\tilde{q}_s}(q) = \begin{cases} 1, & \text{if } -D \le q \le Q_l \\ 1 - \dfrac{q - Q_l}{p_l}, & \text{if } Q_l < q < Q_l + p_l \\ 0, & \text{if } Q_l + p_l \le q \end{cases}$$

The fixed order quantity is *About the same* as forecasted demand in scenarios $s = 2, 5, 8$, (as presented in Table 1) and it is defined as:

$$\mu_{\tilde{q}_s}(q) = \begin{cases} 1 + \dfrac{q}{p_0}, & \text{if } -p_0 \le q \le 0 \\ 1 - \dfrac{q}{p_0}, & \text{if } 0 < q \le p_0 \end{cases}$$

The fixed order quantity is *More* than the forecasted demand in scenarios $s = 3, 6, 9$ (as presented in Table 1) and it is defined as:

$$\mu_{\tilde{q}_s}(q) = \begin{cases} 0, & \text{if } q \le Q_m - p_m \\ 1 - \dfrac{Q_m - q}{p_m}, & \text{if } Q_m - p_m < q < Q_m \\ 1, & \text{if } Q_m \le q \le D_U \end{cases}$$

Similarly, a change in demand time is represented using three linguistic terms: *Earlier*, *At about the same time* and *Later* (shown in Fig. 2). Their membership functions are defined in the same way as the membership functions for changes in demand quantity.

Each fuzzy scenario is associated with a corresponding crisp probability that can be determined based on historical data and the corresponding frequency distribution or specified by the purchase manager based on his/her experience.

4.2. Costs

The following costs are incurred:

- Purchase cost incurred using the standard supplier for order of quantity x_r of r materials:

$$\sum_{r=1}^{R} m_r x_r$$

- Holding cost incurred in scenario $s = 7, 8, 9$, when the fixed demand time is *Later* than the forecasted time and the order for material r is already made using the standard supplier; this means that quantity x_r is in inventory for $T + t_s - y_r - l_r$ time periods:

$$\sum_{r=1}^{R} h_r x_r \left(T + \tilde{t}_s - y_r - l_r \right)$$

- Shortage cost for φ_s^- quantity incurred in scenario $s = 1, 2, 3, 6, 9$, when the fixed demand time is *Earlier* than forecasted and the order is made using the emergency supplier and/or the fixed demand quantity is for *More* than forecasted; this means that the order is made using the standard supplier, and the emergency supplier is used for the additional quantity:

$$\sum_{r=1}^{R} \varphi_s^- \theta_r c_r$$

- Surplus cost for φ_s^+ quantity incurred in scenario $s = 1, 2, 3, 4, 7$, when the fixed demand quantity is for *Less* quantity than forecasted and the order is already made using the standard supplier and/or the fixed demand time is *Earlier* than forecasted and, therefore, the emergency supplier has to be used although the order is already made using the standard supplier:

$$\sum_{r=1}^{R} \varphi_s^+ \theta_r \pi_r$$

The costs incurred in the nine scenarios are presented in Table 2.

For example, in Scenario 3, when the fixed demand is for *More* quantity and *Earlier* than forecasted, the cost includes the shortage cost, because the order has to be made to the emergency supplier. However, the surplus cost is incurred too, because, at the beginning of planning period, the order is made to the standard supplier and it arrives, but later than needed.

4.3. Fuzzy multi-objective optimisation model

To address the problem under consideration, we have used a multi-objective optimisation approach. In addition to the standard objective, which is cost minimisation, two additional objectives are included: maximisation of SN robustness and minimisation of shortages. We measure robustness as the variance of the costs incurred in all the scenarios. The aim is to generate a robust solution which will perform well and incur a reasonable cost in all the uncertainty in scenarios. Shortages impact the manufacturer's capability to operate when there is uncertainty in customer demand changes. Therefore, we calculate the sum of shortages of materials relative to demand in all the scenarios. Generally, higher robustness should incur a higher cost and reduce shortages. Also, a higher number of shortages should incur a higher cost. Therefore, a trade-off between SN cost, robustness and shortages has to be made. However, relationships between these SN performances in the presence of different changes in customer demand are not clear.

The problem is to find the quantity of material r, x_r, to be ordered from the standard supplier, and the time of ordering, y_r, in the planning period, in such a way as to optimise the following objectives:

Fuzzy multi-objective optimisation model

Objective 1. To minimise the **cost**:

To minimise the expected total cost calculated as the sum of the purchase cost of all materials r, $m_r x_r$, and the cost w_s of all scenarios s

$$f2 = \sum_{r=1}^{R} m_r x_r + \sum_{s=1}^{S} p_s w_s \tag{1}$$

Objective 2. To maximise **robustness**:

To minimise the variance of cost w_s incurred in all scenarios s

$$f2 = \sum_{s=1}^{S} p_s [w_s - \sum_{j=1}^{S} p_j w_j]^2 \tag{2}$$

Objective 3. To minimise **shortages**:

To minimise the expected shortages φ_s^- relative to demand quantity and changes in demand quantity, $D + \widetilde{q}_s$, in all scenarios s

$$f3 = \sum_{s=1}^{S} p_s \frac{\varphi_s^-}{D + \widetilde{q}_s} \tag{3}$$

subject to:

$$D + \widetilde{q}_s = x_r \Big/ \theta_r - \varphi_s^+ + \varphi_s^- \tag{4}$$

$$y_r + l_r \le T + \widetilde{t}_s \tag{5}$$

$$x_r, y_r, \varphi_s^+, \varphi_s^-, w_s \ge 0,\ s = 1, 2, \cdots, S,\ r = 1, 2, \cdots, R \tag{6}$$

where

$$w_s = \sum_{r=1}^{R} h_r x_r \left(T + \widetilde{t}_s - y_r - l_r \right) + \sum_{r=1}^{R} \varphi_s^- \theta_r c_r + \sum_{r=1}^{R} \varphi_s^+ \theta_r \pi_r \tag{7}$$

Constraint (4) ensures that customer demand quantity and uncertain changes in demand quantity must be satisfied in each scenario; the sum of customer demand quantity and uncertain changes in demand quantity is equal to the sum of the quantity of materials purchased from the standard supplier and either a shortage of materials requiring purchase from the emergency supplier or the surplus of materials. Constraint (5) means that all materials ordered from the standard supplier should arrive before the forecasted customer demand time and uncertain change in time. Constraint (6) introduces non-negativity of the variables. Equation (7) represents the cost of each scenario consisting of the holding cost, the shortage cost incurred by ordering from the emergency supplier and the surplus cost (penalty cost for surplus of materials).

Due to the fuzziness of changes in customer demand, including the quantity and time, constraints (4) and (5) and equation (7) become fuzzy too. By re-arranging the fuzzy parameters, they become as follows:

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D = \widetilde{q}_s \tag{8}$$

$$y_r + l_r - T \le \widetilde{t}_s \tag{9}$$

$$w_s - \sum_{r=1}^{R} h_r x_r (T - y_r - l_r) - \sum_{r=1}^{R} \varphi_s^- \theta_r c_r - \sum_{r=1}^{R} \varphi_s^+ \theta_r \pi_r = \sum_{r=1}^{R} h_r x_r \widetilde{t}_s \tag{10}$$

The fuzzy multi-objective model given above is a non-linear programming optimisation model with the following decision variables: quantities, x_r, and times of ordering materials from the standard supplier, y_r.

4.4. Transformation of the fuzzy multi-objective model to a crisp single-objective model

Various approaches to solving fuzzy mathematical programming models and fuzzy multi-objective models have been proposed in the literature (Baykasoglu & Gocken, 2008; Zimmermann, 2001). We adapted the method presented by Niknejad and Petrovic (2014) to transform the fuzzy optimisation model given in Section 4.3 into a crisp optimisation model. First, tolerances for violation of fuzzy constraints are defined. Then, a satisfaction degree with regards to achieving the optimal objectives' values and with regards to satisfaction of the fuzzy constraints is introduced. In this way, the original fuzzy optimisation model is transformed into a crisp model which maximises the satisfaction degree. Finally, a standard solver is used to find the optimal solution of the obtained crisp optimisation model.

In our fuzzy multi-objective model, both constraints and objectives are fuzzy and need to be transformed into the corresponding crisp counterparts.

Each fuzzy constraint g is transformed into a crisp constraint by introducing tolerance v of violating the constraint and the satisfaction degree $\alpha \in [0, 1]$of satisfying the constraint. The procedure for transforming a fuzzy constraint into a crisp constraint is given in Appendix A. It is illustrated using as an example of one of the fuzzy constraints of the model.

The fuzzy multi-objectives are handled in a similar way as the fuzzy constraints by introducing the satisfaction degree α. This method is proposed by Zimmermann (2001). If the optimisation problem is to minimise fuzzy objective $\widetilde{f}(x)$, then it can be transformed into the crisp maximisation problem in which the satisfaction degree α has to be maximised. Therefore, the new crisp optimisation problem is to find the maximum α with added constraint (12):

$$\text{Maximise}\ \ \alpha, \alpha \in [0, 1] \tag{11}$$

Such that

$$f(x) \le f^{min} + (1 - \alpha)(f^{max} - f^{min}) \tag{12}$$

where f^{min} and f^{max} are the minimum and maximum values of objective $\widetilde{f}\ (x)$, respectively. In this crisp optimisation problem, the satisfaction degreeα reaches its maximum, $\alpha = 1$, when $\widetilde{f}(x) = f^{min}$, because the problem is to minimise the fuzzy objective $\widetilde{f}(x)$. The satisfaction degree α reaches its minimum, $\alpha = 0$, when $\widetilde{f}(x) = f^{max}$. It decreases monotonously from value 1 to value 0.

In our model, the minimum and maximum values of the three fuzzy objectives are determined as presented in Appendix B.

Finally, using the procedures described in Appendix A and B, the fuzzy multi-objective model is transformed into the single-objective crisp optimisation model of maximising the satisfaction degree α as follows:

<u>Crisp single-objective maximisation model</u>

$$\text{Maximise}\ \ \alpha, \alpha \in [0, 1] \tag{13}$$

Such that

$$f_1 \le f_1^{min} + (1 - \alpha)(f_1^{max} - f_1^{min}) \tag{1i}$$

$$f_2 \le f_2^{min} + (1 - \alpha)(f_2^{max} - f_2^{min}) \tag{2i}$$

$$1 - \alpha \ge \sum_{s=1,4,7} p_s \varphi_s^- \left(1 - (1 - \alpha)\left(1 - \frac{1}{D + Q_l} \right) - (1 - \alpha) v_7 \right) \tag{3i}$$

$$1 - \alpha \ge \sum_{s=2,5,8} p_s \varphi_s^- \left(\frac{1}{D - p_0} - (1 - \alpha)\left(\frac{1}{D - p_0} - \frac{1}{D} \right) - (1 - \alpha) v_8 \right) \tag{3ii}$$

$$1 - \alpha \ge \sum_{S=3,6,9} p_s \varphi_s^- \left(\frac{1}{D + Q_m - p_m} - (1 - \alpha)\left(\frac{1}{D + Q_m - p_m} - \frac{1}{D + Q_m} \right) - (1 - \alpha) v_9 \right) \tag{3iii}$$

The crisp constraints above are derived from three objectives, f_1, f_2 and f_3, given in (1), (2) and (3), respectively. They are obtained following the procedure described in Appendix B. The first two crisp

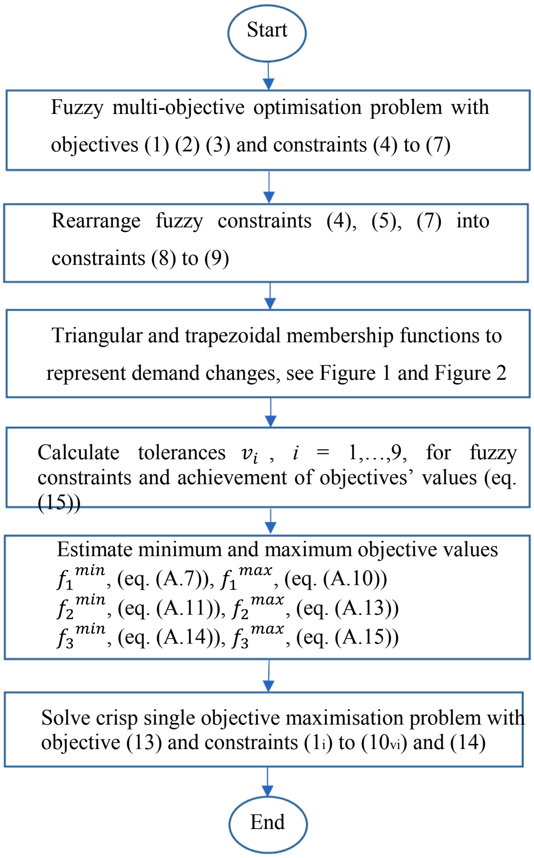

Fig. 3. Flow chart of the proposed method.

constraints (1*i*) and (2*i*) are derived from objectives f_1 and f_2, respectively, and the subsequent three crisp constraints (3*i*), (3*ii*) and (3*iii*) from fuzzy objective f_3.

The crisp constraints from (8*i*) to (8vi) represent fuzzy constraint (8) and are obtained using the procedure given in Appendix A.

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \le -D + (1-\alpha)(Q_l - (-D)) + (1-\alpha)v_1, s = 1,4,7, \; r = 1,2,\cdots,R \tag{8i}$$

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \ge Q_l + p_l - (1-\alpha)p_l - (1-\alpha)v_1, s = 1,4,7, r = 1,2,\cdots,R \tag{8ii}$$

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \le -p_0 + (1-\alpha)p_0 + (1-\alpha)v_2, \; s = 2,5,8, r = 1,2,\cdots,R \tag{8iii}$$

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \ge p_0 - (1-\alpha)p_0 - (1-\alpha)v_2, \; s = 2,5,8, \; r = 1,2,\cdots,R \tag{8iv}$$

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \le Q_m - p_m + (1-\alpha)p_m + (1-\alpha)v_3, \; s = 3,6,9, r = 1,2,\cdots,R \tag{8v}$$

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \ge D_U - (1-\alpha)(D_U - Q_m) - (1-\alpha)v_3, s = 3,6,9, r = 1,2,\cdots,R \tag{8vi}$$

The crisp constraints (9*i*), (9*ii*) and (9*iii*) represent fuzzy constraint (9) where M is a very large number. They are obtained using the procedure given in Appendix A.

$$y_r + l_r - T \le -T + (1-\alpha)(T_e - (-T)) + (1-\alpha)v_4 + |M^*(s-1)^*(s-2)^*(s-3)|, s = 1,2,3, r = 1,2,\cdots,R \tag{9i}$$

$$y_r + l_r - T \le -p_0' + (1-\alpha)p_0' + (1-\alpha)v_5 + |M^*(s-4)^*(s-5)^*(s-6)|, s = 4,5,6, r = 1,2,\cdots,R \tag{9ii}$$

$$y_r + l_r - T \le T_m - p_m' + (1-\alpha)p_m' + (1-\alpha)v_6 + |M^*(s-7)^*(s-8)^*(s-9)|, s = 7,8,9, r = 1,2,\cdots,R \tag{9iii}$$

The crisp constraints from (10*i*) to (10vi) represent fuzzy equation (10). They are obtained using the procedure given in Appendix A.

$$w_s - \sum_{r=1}^R h_r x_r (T - y_r - l_r) - \sum_{r=1}^R \varphi_s^- \theta_r c_r - \sum_{r=1}^R \varphi_s^+ \theta_r \pi_r \le \sum_{r=1}^R h_r x_r [-T + (1-\alpha)(T_e - (-T)) + (1-\alpha)v_4], s = 1,2,3 \tag{10i}$$

$$w_s - \sum_{r=1}^R h_r x_r (T - y_r - l_r) - \sum_{r=1}^R \varphi_s^- \theta_r c_r - \sum_{r=1}^R \varphi_s^+ \theta_r \pi_r \ge \sum_{r=1}^R h_r x_r [T_e + p_e - (1-\alpha)p_e - (1-\alpha)v_4], \; s = 1,2,3 \tag{10ii}$$

$$w_s - \sum_{r=1}^R h_r x_r (T - y_r - l_r) - \sum_{r=1}^R \varphi_s^- \theta_r c_r - \sum_{r=1}^R \varphi_s^+ \theta_r \pi_r \le \sum_{r=1}^R h_r x_r [-p_0' + (1-\alpha)p_0' + (1-\alpha)v_5], \; s = 4,5,6 \tag{10iii}$$

$$w_s - \sum_{r=1}^R h_r x_r (T - y_r - l_r) - \sum_{r=1}^R \varphi_s^- \theta_r c_r - \sum_{r=1}^R \varphi_s^+ \theta_r \pi_r \ge \sum_{r=1}^R h_r x_r [p_0' - (1-\alpha)p_0' - (1-\alpha)v_5], s = 4,5,6 \tag{10iv}$$

$$w_s - \sum_{r=1}^R h_r x_r (T - y_r - l_r) - \sum_{r=1}^R \varphi_s^- \theta_r c_r - \sum_{r=1}^R \varphi_s^+ \theta_r \pi_r \le \sum_{r=1}^R h_r x_r [T_m - p_m' + (1-\alpha)p_m' + (1-\alpha)v_6], s = 7,8,9 \tag{10v}$$

$$w_s - \sum_{r=1}^R h_r x_r (T - y_r - l_r) - \sum_{r=1}^R \varphi_s^- \theta_r c_r - \sum_{r=1}^R \varphi_s^+ \theta_r \pi_r \ge \sum_{r=1}^R h_r x_r [T_U - (1-\alpha)(T_U - T_m) - (1-\alpha)v_6], s = 7,8,9 \tag{10vi}$$

$$x_r, y_r, \varphi_s^+, \varphi_s^-, w_s \ge 0 \tag{14}$$

The crisp model obtained is a mixed-integer non-linear optimisation model with a real decision variable α, integer x_r and real y_r.

Tolerances v_i, $i = 1,\ldots,9$, used in crisp constraints from (1*i*) to (10vi), are set as follows. Tolerance factor V is introduced to calculate acceptable violations of the fuzzy constraints. It is determined empirically; the higher the tolerance factor V, the higher the tolerance for the fuzzy constraints' violation. For example, $V = 0.1$, 0.2 and 0.3 mean that 10%, 20% and 30% of the constraint violation are acceptable, respectively. Tolerances v_i, $i = 1,\ldots,9$, are calculated as the product of the corresponding membership functions of the fuzzy constraints, i.e., the supports of membership functions and tolerance factor V. For example, let us consider the case when the change in customer demand is for *Less* quantity than forecasted (see Fig. 1); the support of the corresponding membership function is $(Q_l + p_l) - (-D)$. In this case, the tolerance for the violation of fuzzy constraint (8) that ensures that customer demand is satisfied when a change in quantity is for *Less* quantity than forecasted is calculated as $v_1 = ((Q_l + p_l) - (-D))^*V$. Further on, when, for example, $V = 0.1$, it means that 10% of the constraint violation is acceptable; this implies that tolerance $v_1 = ((Q_l + p_l) - (-D))^*0.1$. When $V = 0.2$, tolerance v_1 is extended to $((Q_l + p_l) - (-D))^*0.2$, or when $V = 0.3$, tolerance v_1 is extended even more by $((Q_l + p_l) - (-D))^*0.3$. Similarly, if customer demand is for *About the*

Table 3
SN parameter values.

Number of materials R	6
Number of scenarios S	9
Lead time of the standard supplier for material rl_r	12
Unit purchase cost of material r from the standard supplier m_r	7
Unit purchase cost of material r from the emergency supplier c_r	28
Quantity of material r required for one product θ_r	1
Unit penalty cost for the surplus of material $r\pi_r$	18
Holding cost of unit quantity of material r per week h_r	4
Forecasted demand quantity D	200
Forecasted demand time T	24 weeks
Fuzzy change in demand quantity *Less* $\widetilde{q}_{Less}$	$[-D, -D, Q_l, Q_l + p_l]$ = [−200, −200, −150, −150 + 150*0.5] = [−200, −200, −150, −75]
Fuzzy change in demand quantity *About the same* $\widetilde{q}_{About\ \ the\ \ same}$	$[-p_0, 0, p_0]$ = [−100, 0, 100]
Fuzzy change in demand quantity *More* $\widetilde{q}_{More}$	$[Q_m - p_m, Q_m, D_U, D_U]$ = [150–150*0.5, 150, 200, 200] = [75, 150, 200, 200]
Fuzzy change in demand time *Earlier* $\widetilde{t}_{Earlier}$	$[-T, -T, T_e, T_e + p_e]$ = [−24, −24, −12, −12 + 12*0.5] = [−24, −24, −12, −6]
Fuzzy change in demand time *At about the same* $\widetilde{t}_{Atabout\ \ the\ \ same\ \ time}$	$[-p_0', 0, p_0']$ = [−8, 0, 8]
Fuzzy change in demand time *Later* $\widetilde{t}_{Later}$	$[T_m - p_m', T_m, T_U, T_U]$ = [12–12*0.5, 12, 20, 20] = [6, 12, 20, 20]
Probabilities of 9 scenarios	$p_1=p_2=p_3=p_5=p_6=p_7=p_8=p_9 = 0.11$, $p_4=0.12$

same quantity as forecasted (see Fig. 1), the support of the corresponding membership function is $2{*}p_0$. Therefore, $v_2 = (2{*}p_0){*}V$. The remaining tolerances v_i are set in the same manner as follows:

$$v_1 = ((Q_l + p_l) - (-D)){*}V$$

$$v_2 = (2{*}p_0){*}V$$

$$v_3 = (D_U - (Q_m - p_m)){*}V$$

$$v_4 = (T_e + p_e - (-T)){*}V$$

$$v_5 = (2{*}p_0'){*}V$$

$$v_6 = \left(T_U - (T_m - p_m^{'})\right){*}V$$

$$v_7 = (1 - \frac{1}{(D + Q_l)}){*}V$$

$$v_8 = (\frac{1}{D - p_0} - \frac{1}{D}){*}V$$

$$v_9 = (\frac{1}{D + Q_m - p_m} - \frac{1}{D + Q_m}){*}V \tag{15}$$

A flow chart of the proposed method is given in Fig. 3.

5. Analyses of results

Carefully designed experiments are carried out to gain a better understanding of the impact of SN parameters and multi-objectives on SN cost, robustness and shortages. SN hypothetical parameter values in line with the real-world manufacturer data are given in Table 3.

The obtained crisp optimisation model is run using AIMMS (Advanced Integrated Multidimensional Software). This is a general-purpose software for building decision support and optimisation applications. We used a standard laptop Processor Intel(R) Core(TM) i7-5500U CPU @ 2.40 GHz, 2401 Mhz, 16.0 GB (RAM).

The impact of the following parameters on SN cost, robustness and shortages is investigated: (1) tolerance factor V for violating the constraints, (2) unit purchase cost from the emergency supplier, (3) unit surplus cost and (4) scenarios' probabilities. Furthermore, in order to analyse the impact of the multi-objective setting, within each experiment, the model is run for four cases: (a) Case 1 + 2 + 3 – which includes all three objectives, (b) Case 1 + 2 – which includes the cost and robustness objectives, (c) Case 1 + 3 – which includes the cost and shortages objectives and (d) Case 1 – which includes the cost objective, only. Finally, experiments are carried out to analyse computational requirements of the proposed model.

5.1. Impact of tolerances for violating the constraints

The aim of the first experiment is to analyse the impact of the tolerance factor on SN cost. We considered different tolerance factors, V = 0.1, 0.2 and 0.3, which imply 10%, 20% and 30% of achievement of objectives' values and violation of the constraints. Their impact on the costs incurred in the four cases (a) to (d) defined above is given in Fig. 4.

We may conclude that the total cost incurred depends on the tolerance factor V. When $V = 0.1$, the costs incurred in the four cases are smaller than when $V = 0.2$, and are similar to the costs when $V = 0.3$. As the tolerance factor V is subjectively determined and setting $V = 0.3$ would allow a high constraints violation, we decided to set V to 0.1 in the rest of the experiments. The orders recommended by the model when $V = 0.1$ for all four cases are given in Table 4. It might be

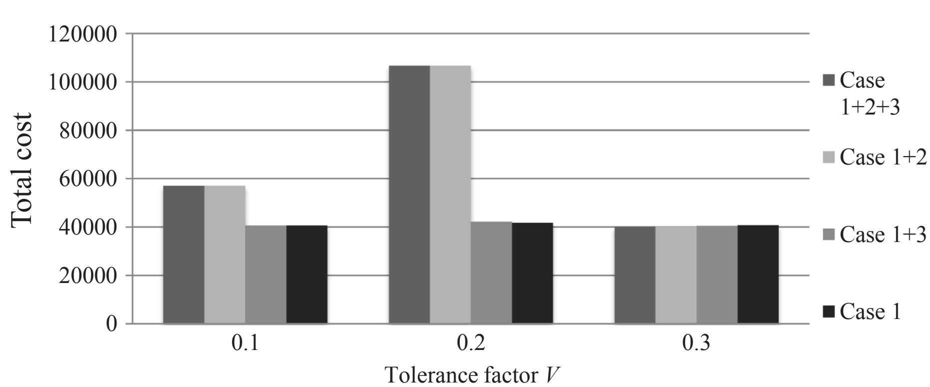

Fig. 4. Total cost incurred for different tolerance factors.

Table 4
Order quantities when $V = 0.1$.

	Order quantity			
Material r	Case 1 + 2 + 3	Case 1 + 2	Case 1 + 3	Case 1
1	106	106	50	49
2	106	106	50	49
3	106	106	50	49
4	106	106	50	49
5	106	106	50	49
6	106	106	50	49

interesting to observe that in this particular SN including robustness as Objective 2 increased the order considerably (from 49 or 50 to 106). In all four cases, $y_r = 0$, $r = 1,\ldots,6$, i.e., it is recommended to order all the materials at the beginning of planning period.

5.2. Impact of the unit purchase cost from the emergency supplier

The aim of these experiments is to analyse the impact of the unit purchase cost from the emergency supplier on SN performance. The experiments are run for three different unit purchase costs from the emergency supplier c_r, $c_r = 28$, $c_r = 70$ and $c_r = 130$. The unit surplus cost is the same in all three experiments, $\pi_r = 18$. The ratio $\frac{c_r}{\pi_r}$ in the three experiments is 1.6, 3.9 and 7.2, respectively. Incurred cost, robustness and shortages are presented in Figs. 5, 6 and 7, respectively. With respect to our measure of robustness, the smaller the variance the more robust the solution. With respect to shortages relative to demand quantity, the smaller the shortages the higher the SN capability to handle changes in customer demand.

We can observe that the total cost in all the experiments is the highest when all three optimisation objectives are included (Case 1 + 2 + 3). Furthermore, when the ratio $\frac{c_r}{\pi_r}$ is high, i.e., when the unit purchase cost from the emergency supplier c_r is high compared to the unit surplus cost,

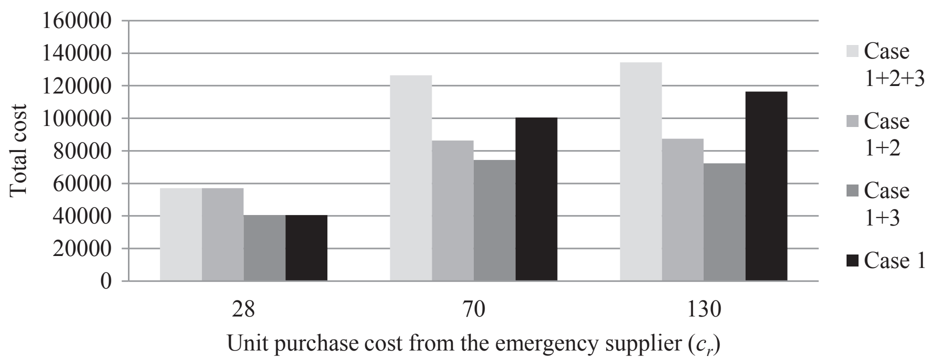

Fig. 5. Total cost for different unit purchase costs from the emergency supplier c_r and $\pi_r = 18$.

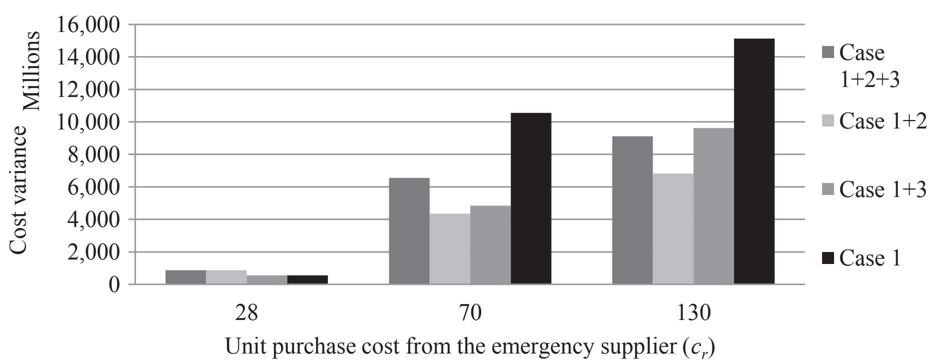

Fig. 6. Robustness for different unit purchase cost from the emergency supplier c_r and $\pi_r = 18$.

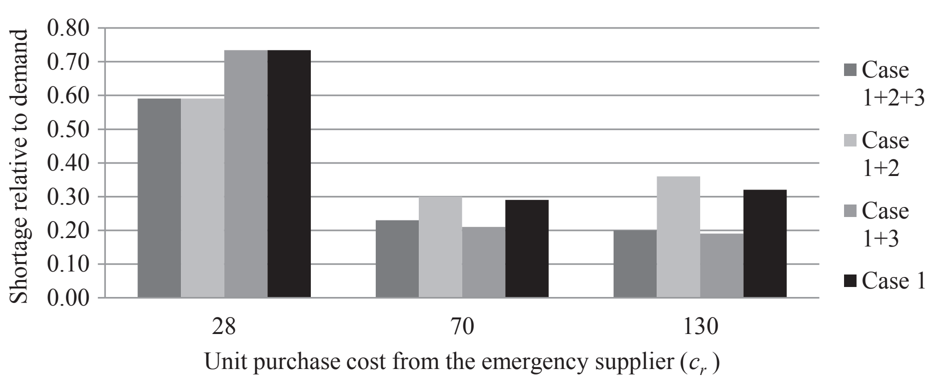

Fig. 7. Shortages for different unit purchase costs from the emergency supplier c_r and $\pi_r = 18$.

Table 5
Order quantities when the unit purchase costs from the emergency supplier are $c_r = 70$ and $c_r = 130$ and the unit surplus cost is $\pi_r = 18$, r = 1,…,6.

Material r	Order quantity							
	$c_r = 70$				$c_r = 130$			
	Case 1 + 2 + 3	Case 1 + 2	Case 1 + 3	Case 1	Case 1 + 2 + 3	Case 1 + 2	Case 1 + 3	Case 1
1	331	290	305	340	366	303	320	384
2	331	290	305	340	366	303	320	384
3	331	290	305	340	366	303	320	384
4	331	290	305	340	366	303	320	384
5	331	290	305	340	366	303	320	384
6	331	290	305	340	366	303	320	384

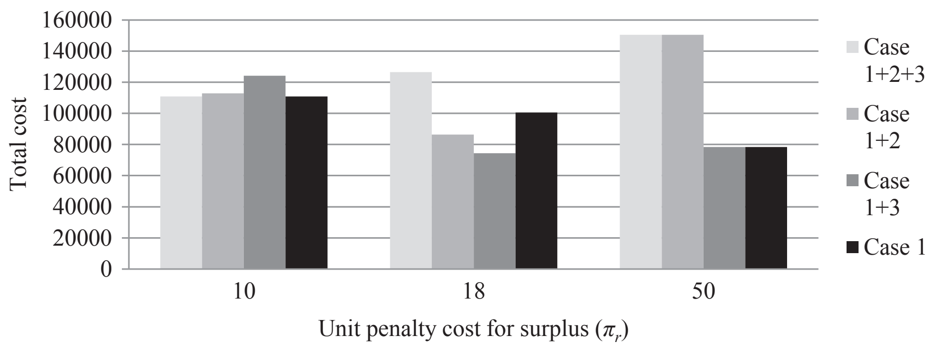

Fig. 8. Total cost for different unit surplus costs π_r and $c_r = 70$.

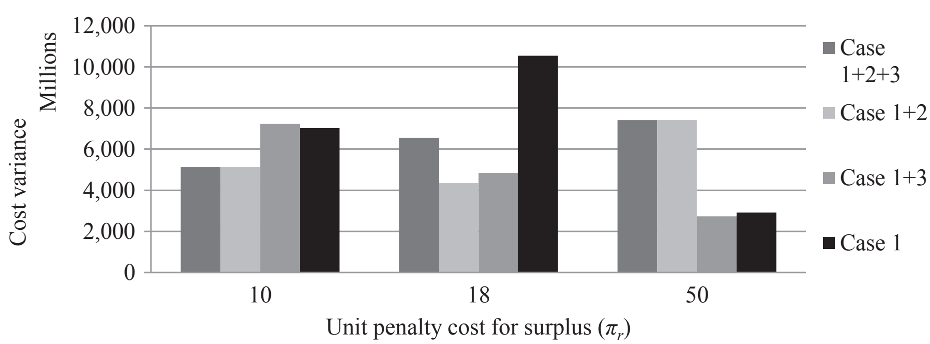

Fig. 9. Robustness for different unit surplus costs π_r and $c_r = 70$.

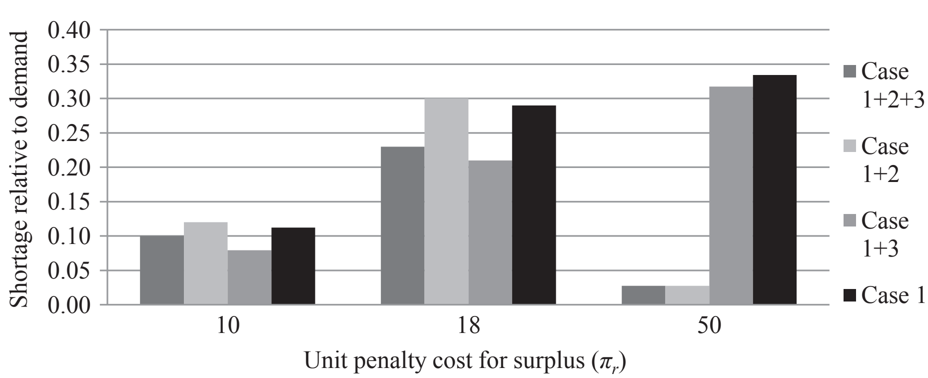

Fig. 10. Shortages for different unit surplus costs π_r and $c_r = 70$.

Table 6
Impact of different scenario probabilities on the costs and decisions on order quantity and order time, when $\pi_r = 18$ and $c_r = 28$.

Case	Scenarios' probabilities	Total cost	Order quantity
i	$p_1 = 0.33$ $p_4 = 0.34$ $p_7 = 0.33$ (scenarios 1, 4, 7 for *Less* quantity)	25,434	58
ii	$p_2 = 0.33$ $p_5 = 0.34$ $p_8 = 0.33$ (scenarios 2, 5, 8 for *About the same* quantity)	57,403	106
iii	$p_3 = 0.33$ $p_6 = 0.34$ $p_9 = 0.33$ (scenarios 3, 6, 9 for *More* quantity)	88,666	106
iv	$p_1 = 0.33$ $p_2 = 0.34$ $p_3 = 0.33$ (scenarios 1, 2, 3 for *Earlier* time)	19,237	106
v	$p_4 = 0.33$ $p_5 = 0.34$ $p_6 = 0.33$ (scenarios 4, 5, 6 for *At about the same time*)	40,284	106
vi	$p_7 = 0.33$ $p_8 = 0.34$ $p_9 = 0.33$ (scenarios 7, 8, 9 for *Later* time)	67,389	106
vii	$p_1 = p_2 = p_3 = p_5 = p_6 = p_7 = p_8 = p_9 = 0.11$ $p_4 = 0.12$ (all 9 scenarios)	57,007	106

Table 7
Impact of different scenario probabilities on the costs and decisions on order quantity and order time, when $\pi_r = 18$ and $c_r = 70$.

Case	Scenarios' probabilities	Total cost	Order quantity
i	$p_1 = 0.33$ $p_4 = 0.34$ $p_7 = 0.33$ (scenarios 1, 4, 7 for *Less* quantity)	137,195	331
ii	$p_2 = 0.33$ $p_5 = 0.34$ $p_8 = 0.33$ (scenarios 2, 5, 8 for *About the same* quantity)	127,606	331
iii	$p_3 = 0.33$ $p_6 = 0.34$ $p_9 = 0.33$ (scenarios 3, 6, 9 for *More* quantity)	114,300	331
iv	$p_1 = 0.33$ $p_2 = 0.34$ $p_3 = 0.33$ (scenarios 1, 2, 3 for *Earlier* time)	28,277	331
v	$p_4 = 0.33$ $p_5 = 0.34$ $p_6 = 0.33$ (scenarios 4, 5, 6 for *At about the same time*)	124,903	331
vi	$p_7 = 0.33$ $p_8 = 0.34$ $p_9 = 0.33$ (scenarios 7, 8, 9 for *Later* time)	215,009	333
vii	$p_1 = p_2 = p_3 = p_5 = p_6 = p_7 = p_8 = p_9 = 0.11$ $p_4 = 0.12$ (all 9 scenarios)	126,481	331

($c_r = 70$ and $c_r = 130$, and $\frac{c_r}{\pi_r} = 3.9$ and $\frac{c_r}{\pi_r} = 7.2$, respectively), the costs incurred in all four cases are higher compared to the costs when the ratio $\frac{c_r}{\pi_r}$ is smaller ($c_r = 70$, and $\frac{c_r}{\pi_r} = 1.6$) (Fig. 5).

Furthermore, a higher impact of the three objectives on SN performance, including total cost, robustness and shortages, can be observed when the ratio $\frac{c_r}{\pi_r}$ is high, i.e., the unit purchase cost from the emergency supplier c_r is high ($c_r = 70$ and $c_r = 130$). Robustness is higher when it is included as Objective 2 as in Case 1 + 2; this means that the variance of the costs incurred in all the scenarios is smaller compared to the other cases (Case 1 + 2 + 3, Case 1 + 3 and Case 1) (Fig. 6). Also, when the ratio $\frac{c_r}{\pi_r}$ is high, a smaller number of shortages is achieved when the shortages are considered as Objective 3 as in Case 1 + 3 (Fig. 7). This means that the higher percentage of demand quantity is satisfied using the standard supplier, i.e., the smaller percentage of demand quantity has to be satisfied using the emergency supplier.

Furthermore, when $c_r = 70$ and $c_r = 130$, the total cost when both robustness and shortages are optimised simultaneously (Case 1 + 2 + 3) is considerably higher than in other cases. This implies that maximising the robustness and minimising shortages of an SN simultaneously can be costly.

Table 5 presents the orders recommended when the unit cost from

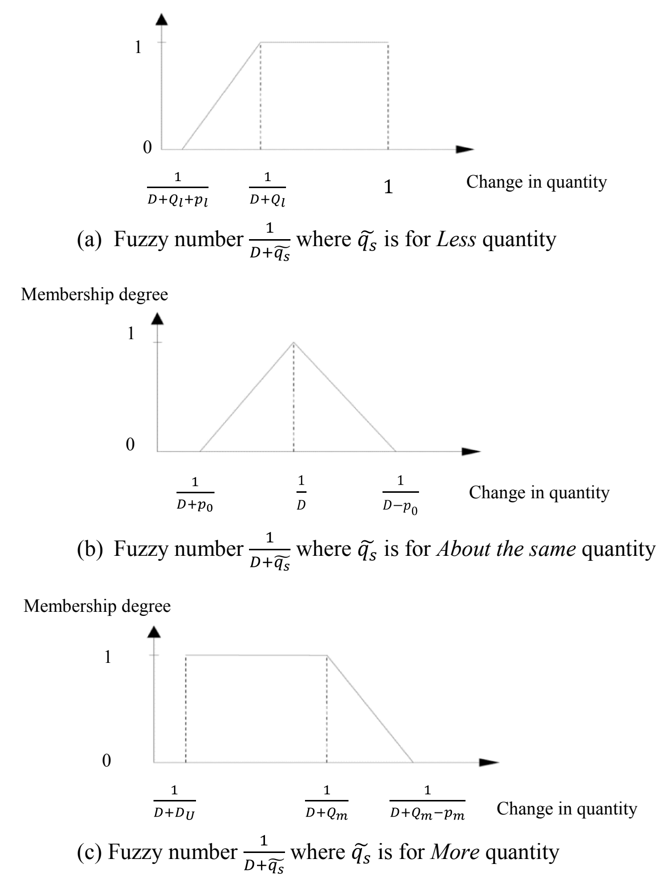

Fig. A.1. Fuzzy number $\frac{1}{D+\widetilde{q}_s}$ in objective f_3.

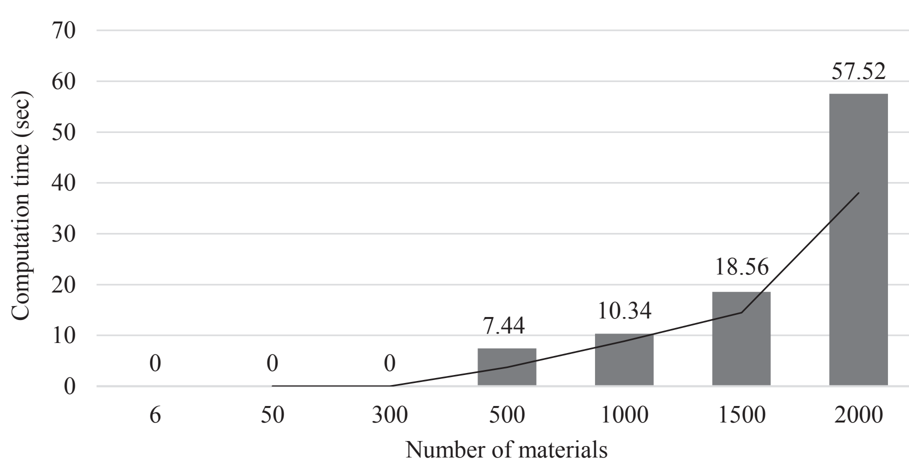

Fig. 11. The computation time required for handling different numbers of materials.

emergency supplier c_r is high, $c_r = 70$ and $c_r = 130$. The orders are considerably higher in all the cases; for example, orders are for 340 and 384 quantities, in Case 1, respectively, compared to orders when c_r is lower, $c_r = 28$; when the orders are for 49 quantities in Case 1 (Tables 4 and 5, respectively). This is expected as the high orders lead to less use of the emergency supplier due to its high cost.

5.3. Impact of the unit surplus cost

These experiments are carried out to analyse the impact of the unit surplus cost on SN performance. The experiments are run for three different unit surplus costs, $\pi_r = 10$, $\pi_r = 18$ and $\pi_r = 50$, when the unit emergency purchase cost is $c_r = 70$. The ratio $\frac{c_r}{\pi_r}$ is 7, 3.9 and 1.4, respectively. The incurred cost, robustness and shortages are presented in Figs. 8, 9 and 10, respectively.

In these experiments, we notice that improving robustness and reducing shortages can be costly. For example, the total costs when robustness and shortages are included as Objectives 2 and 3, respectively (Case 1 + 2 + 3), are highest when the ratio $\frac{c_r}{\pi_r}$ is low, i.e., the unit surplus cost π_r is high ($\pi_r = 18$ and $\pi_r = 50$), compared to Case 1 + 2, Case 1 + 3 and Case 1 (Fig. 8).

We can conclude that including robustness as Objective 2 in Case 1 + 2 leads to better SN robustness than when it is not considered, such as in Case 1 + 3 and Case 1, only when the ratio $\frac{c_r}{\pi_r}$ is high ($\pi_r = 10$, or $\pi_r = 18$ and $\frac{c_r}{\pi_r} = 7$ and $\frac{c_r}{\pi_r} = 3.8$, respectively) (Fig. 9). This can be explained as follows. The high unit emergency purchase cost, $c_r = 70$, results in a small number of shortages and the emergency supplier is rarely used. At the same time, when the unit surplus cost π_r is low ($\pi_r = 10$, or $\pi_r = 18$), its impact on the total cost is small. Therefore, the cost variance in all scenarios is small, which means that robustness is high. With respect to shortages, we can conclude that there are fewer shortages when the minimisation of shortages is included as Objective 3 (Case 1 + 3) compared to other cases, only when the ratio $\frac{c_r}{\pi_r}$ is high (Fig. 10), i.e., the unit surplus cost is low ($\pi_r = 10$ and $\pi_r = 18$). When the ratio $\frac{c_r}{\pi_r}$ is not high, i.e., $\frac{c_r}{\pi_r} = 1.4$ and the unit surplus cost $\pi_r = 50$ is similar to the unit emergency purchase cost $c_r = 70$, orders are decreased due to the high unit surplus cost and, consequently, the number of shortages is increased.

5.4. Impact of scenarios' probabilities

In all the experiments presented in the previous sections, it is assumed that the probabilities of all possible changes in demand quantity and time are equal. However, in practice, the purchase manager might have a subjective experience about which customers are likely to change their forecasted demand and how. Therefore, experiments presented in this section are designed to investigate the impact of the changing probabilities of the scenarios on the decision to be made, i.e., the order quantity and the order time. In two sets of experiments, the unit purchase cost from the emergency supplier c_r is set to $c_r = 28$ and $c_r = 70$, respectively, and the unit surplus cost is $\pi_r = 18$. All other parameters are set to the same values as shown in Table 3. All three objectives, namely the cost, robustness and shortages, are included in the model. In each experiment, the probabilities of nine scenarios are set as follows. In Case i, when $c_r = 28$ (Table 6) and $c_r = 70$ (Table 7), the purchase manager is almost sure that the actual demand quantity placed by the customer will be *Less* than the forecasted demand quantity, the probabilities of scenarios 1, 4 and 7 are set to be 0.33, 0.34 and 0.33, respectively. In this case, the customer can make any changes in the demand time. It is worth mentioning that the sum of these scenarios' probabilities equals to 1. In Case iv, when the purchase manager is almost sure that the actual demand time placed by the customer will be *Earlier* than forecasted, the probabilities of scenarios 1, 2 and 3 are set to be 0.33, 0.34 and 0.33, respectively. The customer can make any change in the demand quantity. Similar explanations can be provided for other experiments. Given the short planning period and long lead time in these experiments, the model suggests that orders should be made at the beginning of the planning period.

Results obtained in the two sets of experiments are given in Tables 6 and 7. The following conclusions can be made:

(a) The scenarios' probabilities can have an impact on the quantities and times of ordering, in particular when the ratio $\frac{c_r}{\pi_r}$ of the unit purchasing cost from the emergency supplier c_r to the unit surplus cost of materials π_r is not high. For example, when $c_r = 28$ and $\pi_r = 18$, the recommended order quantity is $x_r = 106$ in all cases, but drops to $x_r = 58$ when the purchase manager is almost sure that the customer will require *Less* quantity than forecasted. When this ratio is high, for example, $c_r = 70$ and $\pi_r = 18$, then the model recommends higher order quantities from the standard supplier (331). However, the impact of the scenarios' probabilities on the order quantities is not evident in all the cases.

(b) The scenarios' probabilities have a big impact on the total cost incurred. When the ratio $\frac{c_r}{\pi_r}$ of the unit purchasing cost from the emergency supplier to the unit surplus cost of materials is not high, for example, when $c_r = 28$ and $\pi_r = 18$, the cost incurred when the purchase manager is almost sure that the customer will place the fixed order *Later* than forecasted, is 3.5 times higher compared to the cost incurred when it is likely that the customer will place the fixed order *Earlier* (see Cases vi and iv, Table 6). In the former Case, when the emergency supplier has to be used, both the holding cost and shortage cost are incurred. Also, the impact on the total cost is higher when the purchase manager is almost sure that the customer will require *More* quantity than forecasted, compared to *Less* quantity than forecasted, because a bigger purchase has to be made from the emergency supplier. The ratio of the two total costs incurred is 3.45 (see Cases i and iii, Table 6). Furthermore, when the ratio $\frac{c_r}{\pi_r}$ of the unit purchasing cost from the emergency supplier to the unit surplus cost of materials is high, for example, when $c_r = 70$ and $\pi_r = 18$, the impact of the scenarios' probabilities on the total cost becomes even more evident. For example, when the purchase manager is almost sure that the customer will place the fixed order *Later* than forecasted, the total cost incurred is 7.6 times higher than the cost incurred when the purchase manager is almost sure that the customer will place the fixed order *Earlier* (see Cases iv and vi, Table 7). Interestingly, the total cost is smaller if it is likely that the customer will place the fixed order for *More* rather than *Less* quantity. This is because, in the former case, the higher quantity ordered from the standard supplier at the beginning of the planning period leads to a lower quantity of materials purchased from the emergency supplier with a high unit purchase cost. However, there is a higher surplus cost.

5.5. Computational requirements

In order to assess the computational requirements of the proposed model, we are changing the number of materials from 6 to 2000 and record the required computation time. As expected (Fig. 11), the computation time increases with the increase of the number of materials ordered. However, even when number of materials is 2000, it only takes 57.52 s to make the computation. Therefore, it can be concluded that the proposed model can be used effectively in real-world SN decision-making problems with a high number of suppliers/materials to be ordered.

6. Practical and managerial insights

We carried out various experiments in order to get an insight into SN behaviour in the presence of uncertainty in changes in customer demand quantity and time. The impact of different parameters on the SN performance measures is analysed. The following conclusions are made:

- Different tolerances for constraints' violation have an impact on SN performances. In particular, their impact on SN robustness is evident. The setting of a suitable tolerance value depends on various SN parameters and can be determined empirically.
- The robustness metric can be defined as the variance of the costs incurred in different scenarios. It should be considered as an objective in the multi-objective SN model.
- As expected, robustness and shortages can be costly. The proposed model can be used to calculate possible improvements of robustness and reductions of shortages at the price of a higher SN cost.
- The unit purchase cost from the emergency supplier, the unit surplus cost, and, in particular, their ratio are identified as important factors that have an impact on SN cost, robustness and shortages. The impact is higher when this ratio is high, i.e., when the unit purchase cost from the emergency supplier is much higher than the unit surplus cost. In this case, including the objectives of robustness and shortages into the optimisation model can lead to a considerable improvement of these two SN performances.
- Scenarios' probabilities can have a considerable impact on the recommended order quantity and the total cost incurred. The impact is more evident when the ratio of the unit purchase cost from the emergency supplier and unit surplus cost is high.
- The model can be applied to large-scale SNs with a high number of suppliers/materials to be ordered.

7. Conclusions and directions for further research

We consider an SN and different SN performance measures, including cost, robustness and shortages. A new concept of fuzzy scenarios is defined, which represent uncertainty in changes in demand quantity and demand time. Uncertain values of these changes are described by imprecise linguistic terms and modelled using fuzzy sets. We define a new measure of robustness as the variance of the cost incurred in different scenarios. We develop a novel fuzzy multi-objective optimisation model which considers all the fuzzy scenarios. Each objective optimises one of the SN performances, namely total cost, robustness and shortages.

Various experiments are carried out to provide a practical and managerial insight into the relationship between SN parameters and SN performance including cost, robustness and shortages. Results obtained by applying the SN model proved that robustness can be increased and shortages minimised at a higher SN cost. In the case of the high ratio of the unit purchase cost from the emergency supplier to the unit surplus cost, including the objectives of robustness and shortages into the SN optimisation model can lead to a considerable increase of robustness and a decrease of shortages. Also, in this case, the recommended order's quantity and the total SN cost are increased. Finally, it is demonstrated that the model can be applied to large-scale SNs.

Potential future work includes: (1) developing a procedure for generating the fuzzy sets which describe scenarios based on historical data, (2) expanding the model to accommodate uncertainty in probabilities of scenarios which will be specified using linguistic terms, for example, probability is *high* or probability is *around* 0.5, (3) expanding the model to include multi-products and batch discounts and (4) comparing the results obtained using the model to decisions made by the manufacturer to identify potential benefits of the model.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Transformation of a fuzzy constraint into a crisp constraint

We consider three types of fuzzy constraints: (1) $g(x) \le \widetilde{b}$, (2) $g(x) \ge \widetilde{b}$ and (3)$g(x) = \widetilde{b}$, where $\widetilde{b}$ is a fuzzy triangular number or a fuzzy semi-trapezoidal number.

(1) Fuzzy constraint $g(x) \le \widetilde{b}$, where $\widetilde{b}$ is a triangular fuzzy number $[b_1, b_2, b_3]$, is transformed into the following crisp constraint:

$$g(x) \le b_1 + (1-\alpha)(b_2 - b_1) + (1-\alpha)v \tag{A.1}$$

where v is the tolerance for constraint violation and α is degree of constraint satisfaction.

If the constraint satisfaction is fully relaxed, $\alpha = 0$, then $g(x) \le b_2 + v$.

If there is no relaxation of constraint satisfaction, $\alpha = 1$, then $g(x) \le b_1$.

Fuzzy constraint $g(x) \le \widetilde{b}$, where $\widetilde{b}$ is a semi-trapezoidal fuzzy number $[b_1, b_1, b_2, b_3]$, is transformed into the crisp constraint using the same formula (A.1).

(2) Fuzzy constraint $g(x) \ge \widetilde{b}$, where $\widetilde{b}$ is a triangular fuzzy number $[b_1, b_2, b_3]$, is transformed into the following crisp constraint:

$$g(x) \ge b_3 - (1-\alpha)(b_3 - b_2) - (1-\alpha)v \tag{A.2}$$

where v is the tolerance for constraint violation and α is degree of constraint satisfaction.

If the constraint satisfaction is fully relaxed, $\alpha = 0$, then $g(x) \ge b_2 - v$.

If there is no relaxation of constraint satisfaction, $\alpha = 1$, then $g(x) \ge b_3$.

Fuzzy constraint $g(x) \ge \widetilde{b}$, where $\widetilde{b}$ is a semi-trapezoidal fuzzy number $[b_1, b_1, b_2, b_3]$, is transformed into the crisp constraint using the same formula (A.2).

(3) Constraint $g(x) = \widetilde{b}$ is transformed into two constraints, $g(x) \le \widetilde{b}$ and $g(x) \ge \widetilde{b}$. They are transformed into the crisp constraints following the procedure described above.

In all these cases tolerance v is set to $v = (b_3 - b_1)V$, where V is the tolerance factor.

Following this procedure, fuzzy constraints (8), (9) and fuzzy equation (10) of the fuzzy model are transformed into the crisp constraints. For example, let us consider fuzzy constraint (8):

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D = \widetilde{q}_s$$

In scenarios $s = 1$, 4 and 7, change in demand quantity $\widetilde{q}_s$ is *Less* than forecasted and modelled by a semi-trapezoidal fuzzy number $[b1, b1, b2, b3] = [-D, -D, Q_l, Q_l + p_l]$. Fuzzy constraint (8) for these scenarios is transformed into two crisp constraints, (8*i*) and (8*ii*), as follows:

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \leq -D + (1-\alpha)(Q_l - (-D)) + (1-\alpha)v_1, r = 1, 2, \cdots, R$$

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \geq Q_l + p_l - (1-\alpha)(Q_l + p_l - Q_l) - (1-\alpha)v_1, r = 1, 2, \cdots, R$$

where $v_1 = (b_3 - b_1)V = (Q_l + p_l + D)V$.

Further on, in scenarios $s = 2$, 5 and 8, change in demand quantity $\widetilde{q}_s$ is *About the same* as forecasted, and is modelled by a triangular fuzzy number $[-p_0, 0, p_0]$. Fuzzy constraint (8) is transformed into two crisp constraints, (8*iii*) and (8iv), as follows:

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \leq -p_0 + (1-\alpha)p_0 + (1-\alpha)v_2, \quad r = 1, 2, \cdots, R$$

$$\frac{x_r}{\theta_r} - \varphi_s^+ + \varphi_s^- - D \geq p_0 - (1-\alpha)p_0 - (1-\alpha)v_2, \quad r = 1, 2, \cdots, R$$

where $v_2 = 2p_0V$.

A similar transformation of fuzzy constraint (8) into crisp constraints is done for scenarios $s = 3$, 6 and 9, where change in demand quantity is *More* than forecasted, leading to crisp constraints (8v) and (8vi).

Appendix B. Determining the minimum and maximum values of the three objectives

The minimum and maximum values of objective f_1

The minimum cost is incurred when there is no change in quantity or time in the forecasted demand and, therefore, it is equal to the purchasing of $D\theta_r$quantity.

$$f_1^{min} = \sum_{r=1}^{R} m_r D\theta_r \tag{A.3}$$

The maximum cost is incurred in one of the three scenarios: (a) scenario 3, when the customer's fixed demand is *Earlier* and for *More* quantity than forecasted and it incurs both the shortage and the surplus costs, or (b) scenario 7, when the customer's fixed demand is *Later* and for *Less* quantity than forecasted and both the holding and the surplus costs are incurred or (c) scenario 9, when the customer's fixed demand is *Later* and for *More* quantity than forecasted and both the holding and the shortage costs are incurred (see Table 2). However, considering that the unit surplus cost is generally lower that the unit purchasing cost from the emergency supplier, the cost incurred in scenario 7 is lower than the cost incurred in scenario 9, and is, therefore, not considered here.

The cost of scenario 3 includes the emergency purchasing costs for *More* quantity that is fixed *Earlier*, and, also, the surplus cost, because the order is initially made to the standard supplier. The order arrives, but later than needed. Therefore,

Standard purchase cost + scenario 3 cost =

$$\sum_{r=1}^{R} m_r D\theta_r + \sum_{r=1}^{R} c_r (D + D_U)\theta_r + \sum_{r=1}^{R} \pi_r D\theta_r \tag{A.4}$$

The cost of scenario 9 includes the emergency purchasing costs for *More* demand, and the order from the standard supplier. However, this order is needed *Later* than forecasted and, consequently, incurs the holding cost. Therefore,

Standard purchase cost + scenario 9 cost =

$$\sum_{r=1}^{R} m_r D\theta_r + \sum_{r=1}^{R} c_r D_U \theta_r + \sum_{r=1}^{R} h_r D\theta_r (T + T_U - l_r) \tag{A.5}$$

Finally, the maximum cost is the maximum of these two costs:

$$f_1^{max} = \max\{ \sum_{r=1}^{R} m_r D\theta_r + \sum_{r=1}^{R} c_r (D + D_U)\theta_r + \sum_{r=1}^{R} \pi_r D\theta_r,$$

$$\sum_{r=1}^{R} m_r D\theta_r + \sum_{r=1}^{R} c_r D_U \theta_r + \sum_{r=1}^{R} h_r D\theta_r (T + T_U - l_r)\} \tag{A.6}$$

The minimum and maximum values of objective f_2

The minimum robustness is achieved when all the scenarios incur the same cost, i.e., the variance of the scenario costs is 0.

$$f_2^{min} = 0 \tag{A.7}$$

The maximum robustness is achieved when the variance of all scenario costs w_s, $s = 1,\ldots,9$ is the maximum. We approximate the variance to be the maximum when the cost of one scenario reaches its minimum and the cost of another scenario reaches its maximum, with equal probabilities. The minimum of all the scenario costs, w_s, is incurred in scenario 5 when the quantity and the time of fixed and forecasted demand are similar. Therefore,

$$min\ w_s = 0, \text{for} s = 5 \tag{A.8}$$

The maximum costs w_s of all scenarios is incurred either in scenario 3 or in scenario 9, as discussed when calculating ${f_1}^{max}$. It is assumed that the probability of scenario 5 is 0.5 and the probability of both scenario 3 and scenario 9 is 0.5.

Therefore,

$${f_2}^{max} = 0.5^*(variance\ \ of\ \ cost\ \ in\ \ scenario\ \ 3 + variance\ \ of\ \ cost\ \ in\ \ scenario\ \ 9)$$

$$= 0.5^*\left(\sum\nolimits_{r=1}^{R} c_r(D+D_U)\theta_r + \sum\nolimits_{r=1}^{R} \pi_r(D+D_U)\theta_r\right)^2 + 0.5^*\left(\sum\nolimits_{r=1}^{R} c_r D_U\theta_r + \sum\nolimits_{r=1}^{R} h_r D\theta_r(T+T_U-l_r)\right)^2 \tag{A.9}$$

<u>The minimum and maximum values of objective f_3</u>

The minimum and maximum shortages relative to demand quantity are:

$${f_3}^{min} = 0 \tag{A.10}$$

$${f_3}^{max} = 1 \tag{A.11}$$

However, objective $f_3 = \sum_{s=1}^{S} p_s \frac{\varphi_s^-}{D+\widetilde{q}_s}$ is fuzzy and, therefore, it has to be transformed into the corresponding crisp objective. First, fuzzy division $\frac{\varphi_s^-}{D+\widetilde{q}_s}$ is calculated for all scenarios $s = 1,2,\ldots,9$ when the change in demand quantity $\widetilde{q}_s$ is described as *Less*, *About the same* and *More* as follows.

In scenarios $s = 1, 4, 7$, the change in demand quantity $\widetilde{q}_s$ is for *Less* quantity; this is modelled as a semi-trapezoidal fuzzy number$(-D, -D, Q_l, Q_l + p_l)$. Therefore, $D + \widetilde{q}_s$ is also a semi-trapezoidal fuzzy number $(0,\ 0, D+Q_l, D+Q_l+p_l)$. Consequently, $\frac{1}{D+\widetilde{q}_s}$ becomes a semi-trapezoidal fuzzy number $(\frac{1}{D+Q_l+p_l}, \ \frac{1}{D+Q_l}, \frac{1}{0}, \frac{1}{0})$. We conveniently set the boundaries which involve division by 0 to 1 (Fig. A.1 (a)).

In scenarios $s = 2, 5, 8$, the change in demand quantity $\widetilde{q}_s$ is *About the same;* this is presented as a triangular fuzzy number $(-p_o, 0, p_0)$. Therefore, $D + \widetilde{q}_s$ becomes a triangular fuzzy number $(D-p_o, D, D+p_0)$ and $\frac{1}{D+\widetilde{q}_s}$ becomes a fuzzy number $\left(\frac{1}{D+p_0}, \frac{1}{D}, \frac{1}{D-p_0}\right)$ (Fig. A.1(b)).

In scenarios $s = 3, 6, 9$, the change in demand quantity $\widetilde{q}_s$ is for *More* quantity; this is modelled as a semi-trapezoidal fuzzy number$(Q_m - p_m, Q_m, D_U, D_U)$, and, therefore, $D + \widetilde{q}_s$ becomes $(D+Q_m-p_m, D+Q_m, D+D_U, D+D_U)$ and $\frac{1}{D+\widetilde{q}_s}$ becomes a semi-trapezoidal fuzzy number $(\frac{1}{D+D_U}, \frac{1}{D+D_U}, \frac{1}{D+Q_m}, \frac{1}{D+Q_m-p_m})$ (Fig. A.1(c)).

Therefore, fuzzy objective 3 in (3) can be transformed into a crisp objective as follows:

$$f_3 \le f_3^{min} + (1-\alpha)(f_3^{max} - f_3^{min})$$

$$\sum\nolimits_{s=1}^{S} p_s \frac{\varphi_s^-}{D+\widetilde{q}_s} \le 0 + (1-\alpha)(1-0)$$

$$\sum_{s=1}^{S} p_s \varphi_s^- \frac{1}{D+\widetilde{q}_s} \le 1-\alpha \tag{A.12}$$

Following the procedure given in Appendix A, fuzzy constraint (A.12) is transformed into the following three crisp constraints for different scenarios $s = 1,\ldots,9$. They are given in the crisp optimisation model as constraints (3*i*), (3*ii*) and (3*iii*):

$$1-\alpha \ge \sum_{s=1,4,7} p_s\varphi_s^- \left(1-(1-\alpha)\left(1-\frac{1}{D+Q_l}\right)-(1-\alpha)v_7\right) \tag{A.13}$$

$$1-\alpha \ge \sum_{s=2,5,8} p_s\varphi_s^- \left(\frac{1}{D-p_0}-(1-\alpha)\left(\frac{1}{D-p_0}-\frac{1}{D}\right)-(1-\alpha)v_8\right) \tag{A.14}$$

$$1-\alpha \ge \sum_{S=3,6,9} p_s\varphi_s^- \left(\frac{1}{D+Q_m-p_m}-(1-\alpha)\left(\frac{1}{D+Q_m-p_m}-\frac{1}{D+Q_m}\right)-(1-\alpha)v_9\right) \tag{A.15}$$

where v_7, v_8, v_9 are violations introduced for three different changes in demand quantity $\widetilde{q}_s$: *Less*, *About the same* and *More* than forecasted given in Eq. (15).

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