Transportation Research Part E 95 (2016) 124–142

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Multi-objective supplier selection and order allocation under disruption risk

S. PrasannaVenkatesan [a,*], M. Goh [b]

[a] Department of Production Engineering, National Institute of Technology, Tiruchirappalli 620015, TamilNadu, India
[b] NUS Business School, National University of Singapore, Singapore

ARTICLE INFO

Article history:
Received 1 March 2016
Received in revised form 12 August 2016
Accepted 16 September 2016
Available online 3 October 2016

Keywords:
Supplier disruption
Order allocation
Fuzzy AHP
Fuzzy PROMETHEE
MOPSO

ABSTRACT

We formulate a multi-objective MILP model to find the optimal choice of suppliers and their order quantity allocation under disruption risk. Suppliers are evaluated and ranked, based on the preference values obtained using a hybrid fuzzy AHP-fuzzy PROMETHEE. Multi-objective Particle Swarm Optimization is then applied to yield a set of Pareto-optimal solutions for the choice of suppliers and their order allocation. Numerical experimentation suggests that the supplier failure probability affects the expected total cost more than supplier flexibility and loss cost. Sensitivity analysis is performed on the failure probability, the output flexibility, and loss cost of the suppliers.

1. Introduction

The risks in today's supply chain are numerous and are constantly evolving from sources within and outside of the supply chain. In a survey conducted by Deloitte, 71 percent of the respondents view supply chain risk as a crucial factor in their firm's strategic decision-making (Marchese and Paramasivam, 2013). The literature categorizes supply chain risk as either operational or disruption risk (Tang, 2006). Operational risk refers to the inherent uncertainties such as uncertain customer demand, supply, and cost. Disruption risk refers to the major disruptions caused by natural and man-made disasters. The efforts to identify and mitigate supply chain risk have traditionally focused on operational risk as disruption risk were viewed to be (probabilistically speaking) rare events. In recent years, disruption risks have been occurring more frequently and are receiving greater attention as suppliers, particularly those in Asia, tend to be clustered within a single locale for economies of supply. Succumbing to disruption risk can thus lead to a loss in productivity, quality, market share, and reputation for the suppliers and the supply chain (Chopra and Sodhi, 2014). This also leads to an increase in the purchasing and logistics cost as the manufacturers are often compelled to seek and select fresh suppliers quickly from elsewhere and to expedite the shipping to maintain service levels. The twin disasters (Japanese tsunami and Thailand flood) in 2011 attest to this effect. These two events have forced many leading automotive and computer makers to reassess their supply network strategies to effectively mitigate the risks arising from the clustering of suppliers in the two locations, in an attempt to contain costs of transportation and logistics, and to maintain customer service levels. Sourcing under disruption risk is a challenging task for the purchasing firms as it involves a trade-off between minimizing the expected loss of supplier disruption

* Corresponding author.
E-mail addresses: prasanna@nitt.edu (S. PrasannaVenkatesan), mark.goh@nus.edu.sg (M. Goh).

http://dx.doi.org/10.1016/j.tre.2016.09.005
1366-5545/

and maximizing the utility of the suppliers based on their cost, flexibility, and other criteria. We formulate this problem as the multi-objective Supplier Selection and Order Allocation (SSOA) model under disruption risk.

The research on SSOA under disruption risk is scant (Meena and Sarmah, 2014; Sawik, 2014a; Hamdi et al., 2015). For instance, Knemeyer et al. (2009) apply a proactive planning process to identify the key locations for catastrophic risk in a supply chain and to estimate the probability of its occurrence and impact. Chai et al. (2013) review the decision-making techniques in supplier selection. Li et al. (2015) have investigated the effects of decision sequence on a decentralized supply chain in which a supplier faces disruption risk. As such, our contribution to the body of knowledge is to develop a realistic multi-objective model that captures the associated effects arising from disruption risk at the upstream end of the supply chain, which will clearly affect the related transportation and logistics costs. We choose to focus on SSOA particularly in Asia as Asia is the sourcing hub of the global supply chain, and any disruption at this level would have a knock-on effect on the rest of the chain.

This paper is organized as follows. Section 2 reviews the SSOA literature under disruption risk and the methods of fuzzy AHP, fuzzy PROMETHEE, and MOPSO. Section 3 describes the problem and model formulation. Section 4 details the solution approach. Section 5 contains an illustrative example. Section 6 discusses the results. Section 7 concludes the paper.

2. Literature review

2.1. SSOA under disruption risk

Researchers have modeled supply disruption as either a super, semi-super, or unique event (Sarkar and Mohapatra, 2009). A super event causes the suppliers at all locations to be disrupted and cannot deliver the committed quantity to a manufacturer, hence they fail. A semi-super event causes all suppliers at a location to fail while a unique event causes only one supplier at a location to fail. Much of the literature on supply disruption risk concern super and unique events with equal and unequal failure probabilities. Recently, there have been studies considering the region specific supply disruptions due to a semi-super event (Sawik, 2014a, 2014b, 2014c; Kamalahmadi and Mellat-Parast, 2015). Sawik (2014a, 2014b, 2014c) proposed a stochastic Mixed Integer Programming (MIP) approach to integrated supplier selection and customer order scheduling in the presence of supply chain disruption risks. Kamalahmadi and Mellat-Parast (2015) present a two-stage MIP model to minimize the total network cost by integrating SSOA with transportation channel selection. Table 1 shows some recent SSOA models under supply disruption risk. Typically, supply disruption risks are measured by the expected monetary loss (Heckmann et al., 2015). All the SSOA models studied so far are limited to a single objective of either expected total cost minimization, expected worst-case cost minimization (Sawik, 2014c) or profit maximization (Ray and Jenamani, 2016).

Clearly, multi-objective models for SSOA under disruption need further study. Though the decision tree approach is the most common solution method for capturing the different scenarios to help determine the optimum supply base, typically an arbitrary allocation of orders is proposed in increments of 10% (Ruiz-Torres and Mahmoodi, 2006; Meena et al., 2011; Meena and Sarmah, 2016) or 1% (Lee, 2015) for computational expediency. The reason for this is that the computational complexity for SSOA increases with the number of suppliers, locations, failure probabilities, supply capacity, and supplier flexibility. Meena and Sarmah (2013) have shown that SSOA under supply disruption risk is NP-hard and proposed a Genetic Algorithm (GA) for solution. Particle Swarm Optimization (PSO), drawn from swarm intelligence, is another preferred algorithm given its simplicity and performance over the GA (Poli, 2008). In our study, we apply a PSO algorithm to solve a multi-objective SSOA under supply disruption due to super, semi-super, and unique events, in order to reflect a more realistic situation of supplier management under disruption. By employing MOPSO with time varying parameters, our proposed approach is novel as the current literature has yet to provide any evidence of multi-objective supplier selection under disruption using MOPSO.

2.2. Multi-objective SSOA under disruption risk

Several studies have modeled multi-objective SSOA without considering disruption risk (Sawik, 2010; Mafakheri et al., 2011; Jolai et al., 2011; Amin and Zhang, 2012; Azadnia et al., 2015). Torabi et al. (2015) developed a bi-objective mixed possibilistic, two-stage stochastic programming model to build a resilient supply base under operational and disruption risks considering the suppliers' business continuity plans, fortification of the suppliers, and contract with back-up suppliers. Nooraie and Mellat-Parast (2015) developed a multi-objective model to study the relationship among supply chain visibility, supply chain risk, and supply chain cost for a new product under probabilistic demand. Nooraie and Mellat-Parast (2016) further proposed a multi-objective stochastic model to determine the trade-off among the investments in improving supply chain capability and reducing the supply chain risks and to minimize the cost of supply chain disruptions. Khalili et al. (2016) presented a multi-objective mixed possibilistic, two-stage scenario based stochastic programming model to handle SSOA under operational and disruption risks.

However, all of the above studies are limited to the scenarios of individual supplier failures and did not consider region specific supply disruptions. Recently, on region specific supply disruptions, Sawik (2014b) proposed a bi-objective stochastic MIP to optimize the expected value and the expected worst-case value of the cost or customer service of a global supply chain network. Sawik (2016) extended his previous works on stochastic MIP for a bi-objective coordinated selection of

Table 1
Some recent SSOA models under supply disruption risk.

Source	Model details: Objectives – Single	Objectives – Multiple	Decision variables: Number of supplier	Order allocation among suppliers – Equal	Order allocation among suppliers – Unequal	Model Parameters: Cost – FC	Cost – PC	Cost – LC	Cost – PD	Supply failure – Su	Supply failure – Se	Supply failure – Uq – Equal	Supply failure – Uq – Unequal	Output flexibility of suppliers	Solution methodology
Berger et al. (2004)	ETC	–	●	–	–	●	–	●	–	●	–	●	–	–	Decision tree
Zeng et al. (2005)	ETC	–	●	–	–	●	–	●	–	●	–	●	–	–	
Ruiz-Torres and Mahmoodi (2006)	ETC	–	●	–	●	●	●	●	●	–	–	●	●	●	Decision tree and arbitrary order allocation
Ruiz-Torres and Mahmoodi (2007)	ETC	–	●	–	–	●	–	●	–	●	–	●	●	●	Decision tree
Sarkar and Mohapatra (2009)	ETC	–	●	–	–	●	●	●	–	●	●	●	–	–	Decision tree and a tabular method
Meena et al. (2011)	ETC	–	●	●	–	●	●	●	–	●	–	●	–	●	Problem specific algorithm
Meena and Sarmah (2013)	ETC	–	●	–	●	●	●	●	●	●	–	–	●	●	GA
Ruiz-Torres et al. (2013)	ETC	–	●	●		●	●	●	–	–	–	●		●	Decision tree and excel solver
Meena and Sarmah (2014)	ETC	–	●	–	●	●	●	●	●	●	–	–	●	●	GA, BONMIN solver
Sawik (2014a)	ETC/CSL	–	●	–	●	●	●	●	–	–	●	–	●	–	Stochastic MIP
Sawik (2014c)	EWC/WCSL	–	●	–	●	–	●	●	–	●	●	–	●	–	Stochastic MIP
Lee (2015)	ETC	–	●	–	●	●	●	●	●	●	●	–	●	●	Decision tree and arbitrary order allocation
Meena and Sarmah (2016)	ETC	–	●	–	●	●	●	●	●	●	–	–	●	●	Problem specific algorithm
Ray and Jenamani (2016)	ETP	–	●	–	●	–	●	●	●	–	–	–	●	–	Problem specific algorithm

Note: ETC – Expected Total Cost, EWC – Expected Worst-Case Cost, WCSL – Worst-Case Service level, ETP – Expected Total Profit, CSL – Customer Service Level, FC – Fixed Cost, PC – Purchase Cost, LC – Loss Cost, PD – Price Discount, Su – Super event, Se – Semi-super event, Uq – Unique event, BONMIN – Basic open-source Mixed Integer Non-Linear programming.

supply portfolio and scheduling of production and distribution under supply disruptions. Sawik (2014b, 2016) combined the bi-objective model into a single objective using a weighted sum aggregation approach and reported a subset of Pareto optimal solutions. Meta-heuristics such as GA, PSO are found to be efficient in finding a set of Pareto optimal solutions for multi objective optimization.

In our study, we formulate an MILP model to determine the choice of suppliers and the order quantity allocation of the suppliers considering individual and geography-specific regional failures of the suppliers. The objectives are to minimize the expected total cost (ETC) and to maximize the total purchase value (TPV). ETC includes the logistics cost of supplier management, the cost of acquiring raw materials from the suppliers, and the expected supplier loss. TPV represents a manufacturer's utility function based on the preference values (weights) of different suppliers (Mafakheri et al., 2011). TPV is the weighted sum of the order quantities obtained by multiplying the supplier's preference value with the corresponding order quantity. The preference value is a subjective measure used to rank the suppliers considering cost, customer service, and risk. Among the MCDM methods, the outranking approaches are appropriate for ranking applications. PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) is reportedly more stable among the outranking methods (Brans and Mareschal, 2005). Implementing PROMETHEE requires the information on the criteria weights and the choice of preference functions with their parameters. Macharis et al. (2004) have proposed a hybrid AHP (Analytic Hierarchy Process) and PROMETHEE by combining the favorable characteristics of both approaches. To obtain the preference values of the suppliers, we follow Macharis et al. (2004). We use fuzzy AHP (Saaty, 1990) to obtain the criteria and sub-criteria weights and fuzzy PROMETHEE II to rank the suppliers based on preference values. Multi-objective Particle Swarm Optimization (MOPSO) is then used to find the trade-off between minimizing ETC and maximizing TPV.

2.3. Overview of techniques

Fuzzy AHP: Fuzzy AHP is an MCDM tool developed by combining Saaty's (1990) AHP with fuzzy set theory (Zimmermann, 2010). In fuzzy AHP, the linguistic variables or fuzzy numbers are used, as human preferences are often subjective, imprecise, and ambiguous. A fuzzy number is illustrated by a membership function that is a real number between 0 and 1. These membership functions can take several shapes (Ishizaka and Nguyen, 2013). In practice, triangular and trapezoidal membership functions prevail. Several methods have been proposed to handle the fuzzy comparison matrices. Among them is the extent analysis method proposed by Chang (1996) which is commonly used, given its simplicity. Studies have used extent analysis on fuzzy AHP for supplier selection (Lee, 2009; Kilincci and Onal, 2011; Shaw et al., 2012; Kannan et al., 2013; Li et al., 2013; Viswanadham and Samvedi, 2013). Wang et al. (2008) improved the extent analysis method to estimate the true weights from a fuzzy comparison matrix. Zouggari and Benyoucef (2012) have used the improved extent analysis method for supplier selection. In our paper, similarly, we employ Wang et al.'s (2008) method to obtain the criteria and sub-criteria weights (see Appendix A).

Fuzzy PROMETHEE: PROMETHEE is an outranking method that ranks the alternatives according to conflicting criteria (Brans and Mareschal, 2005). Implementing PROMETHEE requires the criteria weights that express the importance of each criterion inside the family of criteria and a decision maker's preference function for each considered criterion. In fuzzy PROMETHEE, the performance of each alternative with respect to each criterion is denoted as a fuzzy number. These fuzzy numbers are then compared and ranked. The maximizing set and minimizing set methods (Chen, 1985) and the centroid method using Yager's index (Goumas and Lygerou, 2000) are some approaches commonly used to rank fuzzy numbers. We will use Yager's ranking index in fuzzy PROMETHEE (Tuzkaya et al., 2010; Yilmaz and Dağdeviren, 2011). Appendix B details the steps of the fuzzy PROMETHEE method.

MOPSO: PSO, developed for continuous optimization, have been applied to multi-objective problems (Lalwani et al., 2013). Kamali et al. (2011) applied PSO on multi-objective buyer-vendor coordination. Che (2012) uses PSO to solve an unbalanced multi-echelon supply chain planning problem. PrasannaVenkatesan and Kumanan (2012a) propose a multi-objective binary PSO algorithm on sourcing under price and exchange rate risks. There is little work thus far on MOPSO for SSOA under disruption. We now detail the steps of MOPSO.

Step 1 Swarm and velocity initialization: The position and velocity of each particle are initialized randomly. A set of feasible particles represents the swarm.

Step 2 Fitness evaluation and ranking: The fitness values of the particles are calculated during the iterations and the non-dominated solutions are stored in an external archive. The density of points around each non-dominated solution in the archive is computed using the crowding distance operator and the solutions in the archive are ranked in descending order of the density values.

Step 3 Local guide (pBest) selection: In MOPSO, the individual experience of the particle is captured in the pBest attribute that corresponds to the best performance attained by a particle in its flight. At the first iteration (t), the current position of particle $p_{i[t]}$ is set as the pBest particle, $pBest_{i[t]}$. In subsequent iterations, $pBest_{i[t]}$ is replaced if $p_{i[t]}$ dominates $pBest_{i[t]}$. If both are mutually non-dominating, then $pBest_{i[t]}$ is selected arbitrarily.

Step 4 Global guide (gBest) selection: The convergence and diversity of the solutions are highly influenced by the global guide selection. The gBest ($g_{i[t]}$) for each particle is selected randomly from a specified top portion of the ranked non-dominated solutions in the archive. Doing so, all elements within the specified top portion have an equal probability to be the guide for the particle.

Step 5 Velocity and position update: The velocity and position update equations are used to update the velocity and position of each particle during the iterations.

3. Problem description and model development

Firms keep a set of preferred suppliers based on cost, quality, and service level. Typically, as shown in Fig. 1, these suppliers tend to be clustered in regions, for reasons of pooling of labor, technology, and others. The disruptions mentioned earlier in this paper have forced the firms to develop contingency plans to mitigate the consequences of the risks due to the geographic clustering of the suppliers. Siting reliable alternative suppliers and sourcing from both preferred and alternate suppliers is practised to minimize the ETC. The ETC includes supplier management cost, purchasing cost, and an expected loss cost (ELC) if a supplier fails due to disruption. Sourcing from preferred suppliers maximizes TPV (Araz et al., 2007; Mafakheri et al., 2011; Jolai et al., 2011; Amin and Zhang, 2012) as a firm tends to allocate as much order quantity as possible to the preferred suppliers. Should these preferred suppliers suffer a disruption, then the ELC incurred by the manufacturer is high albeit the supplier management cost is low. If a part of the order is allocated to alternate suppliers, then ELC is reduced but this may reduce the TPV. The conflicting goals of minimizing the ETC and maximizing the TPV thus require a multi-objective optimization approach.

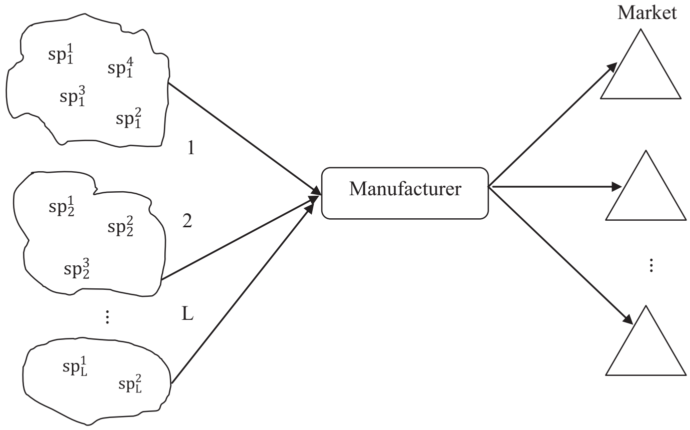

Fig. 1. Supply chain setup.

Model formulation: A multi-objective MILP model is formulated to determine the choice of suppliers and the order allocation among these suppliers, subject to the constraints on capacity and demand. The objectives are to minimize the ETC and to maximize the TPV.

We assume the following in our model:

1. Single product with no quantity discount and a single period planning horizon;
2. Demand of the manufacturer is deterministic;
3. Number of suppliers and their geographical regions, capacities are known and fixed;
4. Cost of acquiring and transporting raw materials from suppliers to manufacturer is known and fixed;
5. A semi-super event is region specific and each region has its disruption probability;
6. Undisrupted supplier(s) will make up the shortfall in the ordered units at no extra cost (Meena and Sarmah, 2013);
7. Each supplier has a different capacity, unique event probability, and compensation potential (which is the ability of the supplier to make up for the shortfall in supply);
8. We estimate the disruption probability of super, semi-super, and unique events by combining the decision maker's opinion with historical data (Knemeyer et al., 2009);
9. Logistics cost of managing suppliers increases with the number of suppliers;

Indices

s	Supplier (s = 1, 2, ..., S)
l	Region (l = 1, 2, ..., L); sp_l^s denotes supplier *s* in region l

Parameters

D	Total demand of raw materials for the planning period
C_s	Capacity of supplier *s*
ts_l	Total number of suppliers in region l
F_s	Fixed cost of managing supplier *s*
r_s	Purchasing cost per item from supplier *s*
r'	Financial loss per item due to the failure of a supplier(s) to deliver
p^{su}	Probability of a super event causing all suppliers to fail due to disruption
p_l^{se}	Probability of a semi-super event causing all suppliers in region l to fail
p_s^{uq}	Probability of a unique event causing supplier *s* to fail due to disruption
Q_s^{min}	Minimum order for supplier *s* as a proportion of the total demand
B(f)	Set of all non-empty subsets of regions l in which all suppliers are disrupted due to a semi-super event with $B(f) = \{B(f_1), B(f_2), \ldots, B(f_L)\}$ where $B(f_1)$ is the subset containing each of a single region in which all suppliers are disrupted; $B(f_2)$ is the subset containing all combinations of any two regions where all suppliers are disrupted; The total number of subsets of regions that can be affected by a semi-super event is $(2^L - 1)$, this being the number of subsets of the set of regions $\{1, 2, \ldots, L\}$ and assuming at least one supplier from a region is selected (Sarkar and Mohapatra, 2009). If three regions l_1, l_2, l_3 are disrupted, then $B(f_1) = \{\{l_1\},\{l_2\},\{l_3\}\}$, $B(f_2) = \{\{l_1,l_2\},\{l_1,l_3\},\{l_2,l_3\}\}$ and $B(f_3) = \{\{l_1,l_2,l_3\}\}$
$B'(f')$	Set of all subsets of regions in which all suppliers are not disrupted due to a semi-super event where

$B'(f') = \{B'(f'_1), B'(f'_2), \ldots, B'(f'_L)\}$ and $B'(f'_1)$ = subset containing undisrupted regions when all the suppliers in one region are disrupted; $B'(f'_2)$ = subset containing undisrupted regions when all suppliers in two regions are disrupted; For example, $B'(f'_1) = \{\{l_2,l_3\},\{l_1,l_3\},\{l_1,l_2\}\}$; $B'(f'_2) = \{\{l_3\},\{l_2\},\{l_1\}\}$ and $B'(f'_3) = \{\}$.

$A(f)$ Set of all non-empty subsets of suppliers who are disrupted due to a unique event, $A(f) = \{A(f_1), A(f_2), \ldots, A(f_S)\}$ where $A(f_1)$ = subset containing each of a single supplier who is disrupted; and $A(f_2)$ = subset containing each of two suppliers who are disrupted, etc. The total number of subsets composed of f_s suppliers that can be subjected to a unique event is $\frac{S!}{f_s!(S-f_s)!}$ where $S = \sum_{l=1}^{L} ts_l$ (Ruiz-Torres and Mahmoodi, 2007). With 8 suppliers, $A(f_1) = \{\{1\},\{2\},\{3\},\{4\},\{5\},\{6\},\{7\},\{8\}\}$; and $A(f_2)$ will have 28 elements with only two suppliers who are disrupted.

$A'(f')$ Set of all subsets of suppliers who are undisrupted due to a unique event, $A'(f') = \{A'(f'_1), A'(f'_2), \ldots, A'(f'_s)\}$, where $A'(f'_1)$ = subset of undisrupted suppliers when one of S suppliers is disrupted;
$A'(f'_1)$ will have 8 elements with 7 undisrupted suppliers in each.
$A'(f'_2)$ = subset of undisrupted suppliers when any two of *S* suppliers are disrupted, etc.

w_s Preference value of supplier obtained from fuzzy PROMETHEE II net flow (Araz et al., 2007);

o_s Supply flexibility index for supplier *s*

Decision variables

X_s 1, if supplier s is selected; 0, else

Q_s Proportion of the total demand assigned to supplier *s*

q_s Compensation received from an undisrupted supplier *s*

Objectives

$$\text{Min} \quad (f_1) = \sum_{s=1}^{S} F_s X_s + \sum_{s=1}^{S} r_s\, Q_s D + ELC \tag{1}$$

where $ELC = \{ELC^{su} + ELC^{se} + ELC^{uq}\}Dr'$, with $ELC^{su} = p^{su}$

$$ELC^{se} = (1-p^{su})\left(\begin{array}{l}\left(I\left(\sum_{i\in B(f_1)}\left(\sum_{s=1}^{ts_i} Q_s\right)_i - \sum_{j\in B'(f'_1)}\left(\sum_{s=1}^{ts_j} q_s\right)_j \geqslant 0\right)\left(\sum_{i\in B(f_1)}\left(\sum_{s=1}^{ts_i} Q_s\right)_i - \sum_{j\in B'(f'_1)}\left(\sum_{s=1}^{ts_j} q_s\right)_j\right)\left(\sum\left(\prod_{i\in B(f_1)} p_i^{se}\prod_{j\in B'(f'_1)}\left(1-p_j^{se}\right)\right)\right)\right) + \\ \left(I\left(\sum_{i\in B(f_2)}\left(\sum_{s=1}^{ts_i} Q_s\right)_i - \sum_{j\in B'(f'_2)}\left(\sum_{s=1}^{ts_j} q_s\right)_j \geqslant 0\right)\left(\sum_{i\in B(f_2)}\left(\sum_{s=1}^{ts_i} Q_s\right)_i - \sum_{j\in B'(f'_2)}\left(\sum_{s=1}^{ts_j} q_s\right)_j\right)\left(\sum\left(\prod_{i\in B(f_2)} p_i^{se}\prod_{j\in B'(f'_2)}\left(1-p_j^{se}\right)\right)\right)\right) \\ + \cdots + \left(I\left(\sum_{i\in B(f_L)}\left(\sum_{s=1}^{ts_i} Q_s\right)_i \geqslant 0\right)\left(\sum_{i\in B(f_L)}\left(\sum_{s=1}^{ts_i} Q_s\right)_i\right)\left(\sum\left(\prod_{i\in B(f_L)} p_i^{se}\right)\right)\right) \text{where } i \neq j\end{array}\right)$$

$$ELC^{uq} = (1-p^{su})\prod_{l=1}^{L}(1-p_l^{se})$$

$$\times\left(\begin{array}{l}\left(I\left(\sum_{m\in A(f_1)}(Q_s)_m - \sum_{n\in A'(f'_1)}(q_s)_n \geqslant 0\right)\left(\sum_{m\in A(f_1)}(Q_s)_m - \sum_{n\in A'(f'_1)}(q_s)_n\right)\left(\sum\left(\prod_{m\in A(f_1)} p_m^{uq}\prod_{n\in A'(f'_1)}(1-p_n^{uq})\right)\right)\right) + \\ \left(I\left(\sum_{m\in A(f_2)}(Q_s)_m - \sum_{n\in A'(f'_2)}(q_s)_n \geqslant 0\right)\left(\sum_{m\in A(f_2)}(Q_s)_m - \sum_{n\in A'(f'_2)}(q_s)_n\right)\left(\sum\left(\prod_{m\in A(f_2)} p_m^{uq}\prod_{n\in A'(f'_2)}(1-p_n^{uq})\right)\right)\right) \\ + \cdots + \left(I\left(\sum_{m\in A(f_L)}(Q_s)_m \geqslant 0\right)\left(\sum_{m\in A(f_L)}(Q_s)_m\right)\left(\sum\left(\prod_{m\in A(f_L)} p_m^{uq}\right)\right)\right) \text{where } m \neq n\end{array}\right)$$

$$\mathrm{Max}\ (\mathrm{f}_2) = \sum_{s=1}^{S} \mathrm{w}_s\, \mathrm{Q}_s \mathrm{D} \tag{2}$$

subject to

$$\mathrm{Q}_s \mathrm{D} \leqslant \mathrm{C}_s \mathrm{X}_s, \quad \forall s \tag{3}$$

$$\sum_{s=1}^{S} \mathrm{Q}_s = 1 \tag{4}$$

$$\mathrm{Q}_s \geqslant \mathrm{Q}_s^{\min} \geqslant 0, \quad \forall s \tag{5}$$

$$0 \leqslant \mathrm{q}_s \leqslant \mathrm{k}_s \mathrm{X}_s;\ \text{where } \mathrm{k}_s = (\mathrm{C}_s/\mathrm{D} - \mathrm{Q}_s)\mathrm{o}_s, \quad \forall s \tag{6}$$

In Eq. (1), the loss due to a super, semi-super, and unique event is denoted as ELC^{su}, ELC^{se}, and ELC^{uq} respectively which are formulated following Meena et al. (2011). TPV shown in Eq. (2) is the weighted sum of the order quantities from the different suppliers which aims to utilize the suppliers based on their preference values (weights) as defined in Araz et al. (2007). The weights denote the preference values of the suppliers obtained using fuzzy AHP and fuzzy PROMETHEE. To maximize TPV, the preferred suppliers are assigned as much orders as possible which results in a higher ELC when a disruption occurs. Eqs. (3) and (4) are the capacity and demand satisfaction constraints for the suppliers respectively. Eq. (5) states that the fraction of the total demand assigned to supplier *s* must be no less than the minimum order assigned to the same supplier. Each undisrupted supplier can compensate a quantity more than its original allocation by an amount $\mathrm{k}_s = (\mathrm{C}_s/\mathrm{D} - \mathrm{Q}_s)\mathrm{o}_s$. Hence, the compensation received from an undisrupted supplier cannot exceed the compensation potential k_s of that supplier as given in Eq. (6). Further, following Meena and Sarmah (2013), we assume that an undisrupted supplier will compensate the shortfall at no extra cost. i.e. undisrupted supplier(s) compensate the unmet demand by supplying an extra amount (q_s) at the same unit purchase cost of the disrupted supplier and the disrupted supplier is not penalized for that. We have made this simplifying assumption so as to formulate a tractable model. The supply flexibility index o_s in Eq. (6) refers to a supplier's ability to compensate for the shortfall should the other suppliers be disrupted (Ruiz-Torres and Mahmoodi, 2006). This index could be measured based on the suppliers' production, logistics capability, capacity commitment to other customers, and geographical proximity. An indicator function I_y is used; $I_y = 1$ if 'y' holds, 0 else.

We show a possible outcome of supplier disruption with 2 regions (l_1,l_2) and 2 suppliers in each region (sp_1^1, sp_1^2, sp_2^1 and sp_2^2), as shown in Table 2. We assume that the total demand is divided equally among the suppliers. The capacities are set to 0.4, 0.3, 0.4, and 0.3 of the total demand (Cs/D) for suppliers $sp_1^1, sp_1^2, sp_2^1,$ and sp_2^2 respectively. The volume flexibility index of the suppliers is set to 1 and hence the compensation received from the four suppliers (if undisturbed) is 0.15, 0.05, 0.15, and 0.05 respectively. The ELC is $\mathrm{P}^{su} * \mathrm{D} * \mathrm{r}'$ when all the suppliers are disrupted due to a super event. If all suppliers in a single region are disrupted due to a semi-super event, then the ELC is the product of the failure probability and the quantity loss. In this illustration, the demand allotted to suppliers of Regions 1 and 2 is 0.5 and 0.5 respectively. The loss in the event of a regional disruption of suppliers is computed, after subtracting the order allotted to the suppliers in the disrupted region from the compensation received from the undisrupted region. In short, when the suppliers from Region 1 are disrupted, 0.3 (=0.25 + 0.25 – 0.15 – 0.05) is the actual loss after a compensation of 0.2 is received from the undisrupted Region 2 suppliers. Here, ELC is zero as the undisrupted suppliers can compensate the shortfall when a single supplier is disrupted due to a unique event. The proposed model needs a heuristic as finding the solution considering all possible outcomes of supplier disruptions is computationally cumbersome given the number of suppliers, locations, failure probabilities, supplier capacity and flexibility.

Table 2
Possible outcome for supplier disruption with 2 regions (l_1, l_2) and 2 suppliers in each region.

Event	Set of suppliers		Probability	ELC
	Disturbed	Undisturbed		
Super	All	None	P^{su}	$\mathrm{P}^{su} * \mathrm{D} * \mathrm{r}'$
Semi-super	$\mathrm{B}(\mathrm{f}_1) = \{\{\mathrm{l}_1\},\{\mathrm{l}_2\}\}$	$B'(f_1') = \{\{\mathrm{l}_2\},\{\mathrm{l}_1\}\}$	$(1-\mathrm{P}^{su})P^{se}_{l1}(1-P^{se}_{l2}) + (1-\mathrm{P}^{su})(1-P^{se}_{l1})P^{se}_{l2}$	$\{(1-\mathrm{P}^{su})P^{se}_{l1}(1-P^{se}_{l2})(0.5-0.2)$ $+(1-\mathrm{P}^{su})(1-P^{se}_{l1})$ $P^{se}_{l2}(0.5-0.2)\}\mathrm{D}\mathrm{r}'$
Unique	$\mathrm{A}(\mathrm{f}_1) = \{\{sp_1^1\},\{sp_1^2\},$ $\{,sp_2^1\},\{sp_2^2\}\}$	$A'(f_1') = \{\{sp_1^2, sp_2^1$ and $sp_2^2\},$ $\{sp_1^1, sp_2^1$ and $sp_2^2\},$ $\{sp_1^1, sp_1^2$ and $sp_2^2\},$ $\{sp_1^1, sp_1^2$ and $sp_2^1\}\}$	$(1-\mathrm{P}^{su})(1-P^{se}_{l1})(1-P^{se}_{l2})(P^{uq}_1)$ $(1-P^{uq}_2)(1-P^{uq}_3)(1-P^{uq}_4)$ $+\cdots+(1-\mathrm{P}^{su})(1-P^{se}_{l1})(1-P^{se}_{l2})$ $(P^{uq}_4)(1-P^{uq}_1)(1-P^{uq}_2)(1-P^{uq}_3)$ where 1, 2, 3 and 4 denote the four suppliers in set $\mathrm{A}(\mathrm{f}_1)$ respectively.	0

4. Method

Fig. 2 shows the flowchart for the proposed approach. The suppliers are evaluated and ranked based on the preference value obtained using the hybrid fuzzy AHP-fuzzy PROMETHEE in Phase I. In Phase II, an MOPSO is developed to find the choice of suppliers and the order allocation among them. The fuzzy AHP, fuzzy PROMETHEE, and MOPSO are coded in Matlab 7.10.

4.1. Proposed fuzzy AHP

The supplier evaluation and ranking involves alternatives $(a_1, \ldots, a_A)$ and criteria $(c_1, \ldots, c_C)$. The alternatives denote a finite number of suppliers to be ranked. The criteria refer to the decision factors that are used to evaluate the suppliers. The criteria weights $(W_1, \ldots, W_c)$ denote the relative importance of each criterion.

Identification of goal, criteria, and alternatives: Fig. 3 shows the decision hierarchy of supplier evaluation and ranking. From the literature, three main criteria and thirteen sub-criteria are identified (Lee, 2009; Mafakheri et al., 2011; Zouggari and Benyoucef, 2012; Kannan et al., 2013; Osiro et al., 2014).

Determine criteria and sub-criteria weights: The linguistic variables shown in Table 3 are used to carry out pair-wise comparisons between the criteria and sub-criteria (Jolai et al., 2011). The fuzzy pair-wise comparison matrices are converted into crisp matrices and the consistency of each matrix is verified. The criteria and sub-criteria weights are then determined using the improved extent analysis method (Wang et al., 2008).

4.2. Proposed fuzzy PROMETHEE

Construct fuzzy evaluation matrix: The linguistic variables shown in Table 4 are used to evaluate the suppliers considering each criterion (Yilmaz and Dağdeviren, 2011). In this paper, fuzzy numbers are presented in the form $x = (n, a, b)_{LR}$ as proposed by Dubois and Prade (1978) which is equivalent to the conventional tuple form of triangular numbers (l, m, u) such that $(l, m, u) = [n - a, n, n + b]$. The corresponding membership function is given by Fig. 4. The defuzzified form of the given fuzzy number is then computed using the centroid method (Goumas and Lygerou, 2000).

Apply preference functions with threshold for each criterion: The linear preference function, commonly found in the literature, with preference p and indifference threshold q is selected for all the criteria. The linear preference function for the alternatives (a_1, a_2) is defined as shown in Eq. (7). When using the fuzzy numbers in PROMETHEE, the membership function shown in Fig. 4 can be converted to Eq. (7). In Eq. (7), the values of p and q are crisp numbers and the magnitude of the triangular fuzzy number is calculated using the Yager index. The outranking flows are then computed and the suppliers are ranked based on the PROMETHEE II net flow (Appendix B).

$$P_j(a_1, a_2) = \begin{cases} 0, & \text{if } (n - a_1) \leqslant q \\ (n, a_1, a_2) - q/p - q, & \text{if } q < (n - a_1) \text{ and } (n + a_2) \leqslant p \\ 1, & \text{if } (n + a_2) > p \end{cases} \tag{7}$$

4.3. MOPSO

The parameters of the proposed MOPSO algorithm are swarm size (N), maximum number of iterations (max_it), external archive size (ex_ar), inertia weights, and acceleration coefficients.

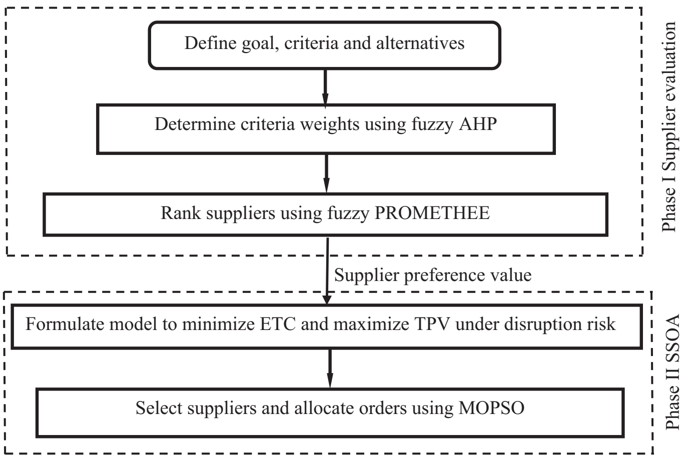

Fig. 2. Flow chart of proposed approach.

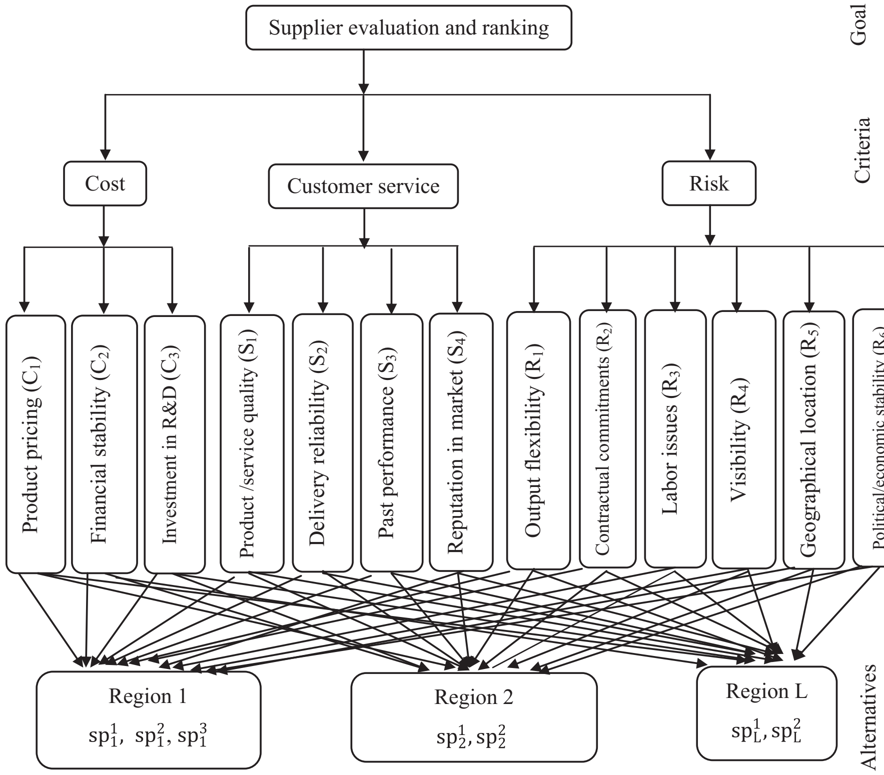

Fig. 3. Decision hierarchy structure for supplier evaluation.

Table 3
Linguistic variables for pair-wise comparison of criteria and sub-criteria.

Linguistic variable	Triangular fuzzy number
Equal importance	(1,1,3)
Moderately more important	(1,3,5)
Strongly more important	(3,5,7)
Very strongly important	(5,7,9)
Extremely more important	(7,9,9)

Table 4
Linguistic variables for evaluating suppliers.

Very Bad (VB)	Triangular fuzzy number
Bad (B)	$(0,0,0.15)_{LR}$
Weak (W)	$(0.15,0.15,0.15)_{LR}$
Medium (M)	$(0.30,0.15,0.20)_{LR}$
Good (G)	$(0.50,0.20,0.15)_{LR}$
Very Good (VG)	$(0.80,0.50,0.20)_{LR}$
Excellent (E)	$(1,0.20,0)_{LR}$

Particle representation and swarm initialization: In the MOPSO algorithm, each particle is a feasible allocation of demand to the suppliers. The length of a particle depends on the number of suppliers and each bit of a particle represents the fraction of demand assigned to a supplier. An example of a particle for eight suppliers located in three regions is shown in Fig. 5. There are three suppliers each in Regions 1 and 2, and two suppliers in Region 3. The maximum demand is then allocated to supplier 1 in Region 1 but supplier 2 in Region 3 is not selected. The fitness values of the particles are calculated and the non-dominated solutions (NDS) are stored in an external archive (ex_ar). A single pBest is maintained based on the dominance relation among the current position of a particle ($P_{i[t]}$) and the previous best. The gBest for each particle is selected randomly from a subset of the NDS ranked using the crowding distance method.

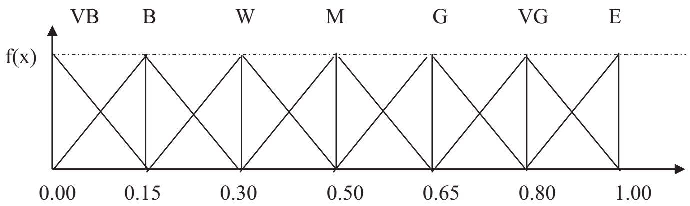

Fig. 4. Membership functions of triangular fuzzy numbers.

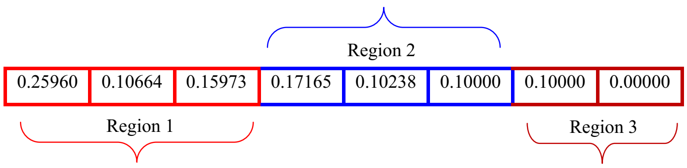

Fig. 5. Representation of a particle for proposed problem.

Velocity and position update: The velocity update relation is given in Eq. (8) where r_1 and r_2 are uniformly distributed on $(0, 1)$. The inertia weight ω_t is allowed to decrease linearly with iteration, from the initial value ω_1 to the final value ω_2 (see Eq. (9)). This ensures global exploration of the search space at the initial stages and local exploration at the later stages. C_{1t} is allowed to decrease from its initial value of C_{1i} to a final value C_{1f} as shown in Eq. (10). C_{2t} is allowed to increase from its initial value of C_{2i} to a final value C_{2f} as shown in Eq. (11). The particle's position is updated using Eq. (12). After a position update, the particles are evaluated for feasibility. Infeasible particles are repaired subject to the constraints on demand, capacity, and minimum order allocation.

$$V_{i[t+1]} = \omega_t V_{i[t]} + r_1 C_{1t}(pBest_{i[t]} - P_{i[t]}) + r_2 C_{2t}(ex\_ar[gBest_{i[t]} - P_{i[t]}]) \tag{8}$$

$$\omega_t = (\omega_1 - \omega_2)(\max\_it - t)/(\max\_it) + \omega_2 \tag{9}$$

$$C_{1t} = (C_{1f} - C_{1i})(t/\max\_it) + C_{1i} \tag{10}$$

$$C_{2t} = (C_{2f} - C_{2i})(t/\max\_it) + C_{2i} \tag{11}$$

$$P_{i[t+1]} = P_{i[t]} + V_{i[t+1]} \tag{12}$$

5. Numerical example

We now demonstrate the proposed model, using data drawn from the literature where possible and available. A manufacturer plans to procure materials from a set of suppliers based in three regions. The suppliers in Region 1 are established with a good market reputation and are the primary procurement source for the materials. To avoid depending on a single supply region, the manufacturer decides to consider suppliers from Regions 2 and 3, as Region 1 is prone to supply disruption risks. The suppliers in Region 3 are located nearer the manufacturer albeit new and are more expensive than the other regions. The suppliers in Regions 1 and 2 are located outside the manufacturer's geographical proximity. Total demand for the manufacturer is set at 8000 units. The minimum order quantity for any supplier is set at 10% of the total demand (Ruiz-Torres and Mahmoodi, 2006). Table 5 shows the capacity, failure probabilities, supply flexibility index of the suppliers, supplier management cost, and unit cost of the materials.

Region 1 has established suppliers with higher capacities. Region 3 has new suppliers and hence the cost of meetings, negotiation and monitoring the quality results in a higher logistics cost on supplier management. The failure probability values for the super, semi-super, and unique events are taken from the literature and presented in Table 1. The loss per unit is set to vary between 2 and 4 times of the purchase cost of the material (Ruiz-Torres and Mahmoodi, 2006). The fuzzy pairwise comparisons matrices for the main- and sub-criteria are constructed using the linguistic variables reported in Section 4.1. The value of λ_{max} and the consistency ratio are computed for all the matrices as shown in Table 6. The suppliers are evaluated on the criteria using the linguistic variables reported in Section 4.2 and Table 7 shows the evaluation matrix.

Table 5
Data.

Supplier		Supplier capacity	Failure probability of event			Output flexibility index	Supplier management cost ($)	Unit purchase cost ($)
			Super	Semi-super	Unique			
Region 1	sp_1^1	3000	0.010	0.030	0.050	0.7	2000	12
	sp_1^2	2400			0.100	1.0	1500	13
	sp_1^3	3200			0.150	0.8	1000	14
Region 2	sp_2^1	1600		0.025	0.100	0.7	2000	15
	sp_2^2	1200			0.150	0.7	2500	18
	sp_2^3	1800			0.050	0.5	1200	16
Region 3	sp_3^1	1500		0.020	0.060	0.4	3500	18
	sp_3^2	1200			0.030	0.4	2500	15

Table 6
Fuzzy pair-wise comparison matrix of supplier evaluation criteria and sub-criteria.

Main criteria: Supplier evaluation

Criteria	Cost	Customer service	Risk
Cost	(1,1,1)	(1,3,5)	(1,1,3)
Customer Service	(1/5,1/3,1)	(1,1,1)	(1,1,3)
Risk	(1/3,1,1)	(1/3,1,1)	(1,1,1)
		λ_{max} = 3.0536	CR = 0.04623

Sub-criteria: Cost

Sub-criteria	C_1	C_2	C_3
C_1	(1,1,1)	(1,3,5)	(5,7,9)
C_2	(1/5,1/3,1)	(1,1,1)	(3,5,7)
C_3	(1/9,1/7,1/5)	(1/7,1/5,1/3)	(1,1,1)
		λ_{max} = 3.0092	CR = 0.00793

Sub-criteria: Customer service

Sub-criteria	S_1	S_2	S_3	S_4
S_1	(1,1,1)	(1,1,3)	(3,5,7)	(1,3,5)
S_2	(1/3,1,1)	(1,1,1)	(5,7,9)	(5,7,9)
S_3	(1/7,1/5,1/3)	(1/9,1/7,1/5)	(1,1,1)	(1,1,3)
S_4	(1/5,1/3,1)	(1/9,1/7,1/5)	(1/3,1,1)	(1,1,1)
			λ_{max} = 4.2216	CR = 0.08299

Sub-criteria: Risk

Sub-criteria	R_1	R_2	R_3	R_4	R_5	R_6
R_1	(1,1,1)	(3,5,7)	(3,5,7)	(1,1,3)	(1,1,3)	(3,5,7)
R_2	(1/7,1/5,1/3)	(1,1,1)	(3,5,7)	(1/5,1/3,1)	(1/7,1/5,1/3)	(1,3,5)
R_3	(1/7,1/5,1/3)	(1/7,1/5,1/3)	(1,1,1)	(1/5,1/3,1)	(1/7,1/5,1/3)	(1,1,3)
R_4	(1/3,1,1)	(1,3,5)	(1,3,5)	(1,1,1)	(1,3,5)	(1,3,5)
R_5	(1/3,1,1)	(3,5,7)	(3,5,7)	(1/5,1/3,1)	(1,1,1)	(1,3,5)
R_6	(1/7,1/5,1/3)	(1/5,1/3,1)	(1/3,1,1)	(1/5,1/3,1)	(1/5,1/3,1)	(1,1,1)
			λ_{max} = 6.5568		CR = 0.089085	

6. Results and discussion

6.1. Supplier evaluation using fuzzy AHP and fuzzy PROMETHEE

Fuzzy AHP: The proposed fuzzy AHP is applied to the main criteria yielding the results found in Appendix A, where $\widetilde{S}_i$ (i = 1, 2, 3) corresponds to the fuzzy synthetic extant value and 'V' the minimum degree of possibility.

$$\widetilde{S}_1 = (0.2727, 0.4839, 0.6995),\ \widetilde{S}_2 = (0.1549, 0.2258, 0.5172),$$
$$\widetilde{S}_3 = (0.1064, 0.2903, 0.3659)$$
$$V(\widetilde{S}_1 \geqslant \widetilde{S}_2, \widetilde{S}_3) = \min(1, 1) = 1;\ V(\widetilde{S}_2 \geqslant \widetilde{S}_1, \widetilde{S}_3) = \min(0.4865, 0.8643) = 0.4865;$$
$$V(\widetilde{S}_3 \geqslant \widetilde{S}_1, \widetilde{S}_2) = \min(0.3249, 1) = 0.3249.$$

The weights for the main criteria are then computed. The proposed approach is repeated for all sub-criteria. Table 8 provides the weights of the main- and sub-criteria obtained using fuzzy AHP. The results suggest that product price [C_1],

Table 7
Supplier linguistic evaluations.

Alternative	Criteria												
	C_1	C_2	C_3	S_1	S_2	S_3	S_4	R_1	R_2	R_3	R_4	R_5	R_6
sp_1^1	E	VG	M	G	G	G	VG	G	VG	E	W	W	G
sp_1^2	VG	VG	M	VG	M	G	G	G	VG	G	M	B	G
sp_1^3	G	VG	G	E	M	E	VG	G	VG	VG	W	M	VG
sp_2^1	G	G	M	G	G	M	G	M	VG	G	M	G	G
sp_2^2	G	M	M	G	M	G	VG	M	VG	M	M	G	M
sp_2^3	VG	G	M	VG	G	G	G	G	VG	G	W	M	G
sp_3^1	M	VG	W	E	E	E	E	M	B	W	B	VG	G
sp_3^2	W	M	W	G	G	G	G	W	B	M	B	G	G

Table 8
Weights of criteria and sub-criteria for supplier evaluation.

Main criteria	Weight of main criteria (a)	Sub-criteria	Local weight of sub-criteria (b)	Global weight of sub-criteria c = (a) ∗ (b)
Cost	0.55207	C_1	0.56411	0.31143
		C_2	0.18546	0.10239
		C_3	0.25043	0.13825
Customer service	0.26859	S_1	0.28471	0.07647
		S_2	0.57783	0.1552
		S_3	0.03280	0.00881
		S_4	0.10466	0.02811
Risk	0.17934	R_1	0.29990	0.05378
		R_2	0.17281	0.03099
		R_3	0.00716	0.00128
		R_4	0.24311	0.04360
		R_5	0.26269	0.04711
		R_6	0.01433	0.00257

delivery reliability [S_2], and supply flexibility of suppliers [R_1] are significant among the criteria cost, customer service, and risk respectively.

Fuzzy PROMETHEE: The supplier linguistic evaluation matrix is converted to triangular fuzzy numbers using the scale reported in Table 4. The difference between the alternatives for each criterion is then computed, and the magnitude of the difference is calculated using the Yager index. In this paper, the preference and indifference thresholds for the linear preference functions are set as 0.6 and 0 respectively, following Yilmaz and Dağdeviren (2011). The aggregated preference indices are then computed using the sub-criteria weights. The positive (Φ^+), negative (Φ^-), and net (Φ) outranking flows for the alternatives are found from the aggregated preference indices.

Table 9 contains the results. Based on the net flow, the complete ranking of the suppliers is obtained. Suppliers sp_1^1, sp_1^3, and sp_2^1 are ranked as the top three preferred suppliers followed by sp_2^2, sp_2^3, sp_3^1, sp_1^2, and sp_3^2.

6.2. Supplier order allocation using MOPSO

The parameters of the proposed algorithm are described below.

Swarm size: Deb (2001) has reported that the population (swarm) size increases exponentially with the number of objectives in a multi-objective optimization problem. In our paper, the swarm size is set as 500 considering the best values of the two objectives obtained during the search.

Maximum number of iterations: The maximum number of iterations is set at 3000 considering the archive growth and variations in the extreme values of the two objectives during the search. Based on random trials, the inertia weight is set to vary linearly from 0.3 to 1.0, and the acceleration coefficients are set as $C_{1i} = 1.5$, $C_{1f} = 0.5$, $C_{2i} = 0.5$, $C_{2f} = 1.5$. For the multi-objective optimization algorithm, the ratio of population (swarm) size to the maximum size of the archive is frequently set as 4 to 1 (Lei, 2008). In this paper, the maximum archive size is set to half the swarm size considering the archive growth.

Global guide selection from the archive: The global guide is selected from the top 75% of the ranked archive to enable the swarm to move towards the sparsely populated regions of the search space (PrasannaVenkatesan and Kumanan, 2012b). If there is no change in the extreme values of the Pareto optimal solutions for 50 consecutive iterations, then 20% of the particles in the swarm are randomly replaced with newly generated particles. This avoids a premature convergence to the local Pareto optimal solutions.

Pareto optimal solutions: Table 10 shows the Pareto optimal solutions obtained for the example using the proposed algorithm. ETC varies from $176,707 to $205,811 and TPV from −6.365 to 451.424. In the minimum cost solution, to avoid a loss

Table 9
Positive, negative, and net flows for alternatives using fuzzy PROMETHEE.

Alternative	sp_1^1	sp_1^2	sp_1^3	sp_2^1	sp_2^2	sp_2^3	sp_3^1	sp_3^2	Φ^+
sp_1^1	0	0	0	0	0.0013	0	0.3127	0.3665	0.0972
sp_1^2	0	0	0	0	0	0	0.0013	0.0538	0.0079
sp_1^3	0	0	0	0.0088	0	0	0.1383	0.5036	0.0929
sp_2^1	0.0471	0.0471	0	0	0	0	0.0013	0.3114	0.0581
sp_2^2	0.0471	0.0471	0	0	0	0	0	0.3114	0.0580
sp_2^3	0	0	0	0	0	0	0.0013	0.0538	0.0079
sp_3^1	0	0.1552	0.1552	0.0088	0.1552	0	0	0	0.0678
sp_3^2	0.047	0.0471	0	0	0	0	0	0	0.0135
Φ^-	0.0202	0.0424	0.0222	0.0025	0.0224	0	0.0650	0.2286	
Φ	0.0770	−0.0345	0.0708	0.0556	0.0356	0.0079	0.0028	−0.2152	

Table 10
Pareto optimal solutions using proposed MOPSO.

ETC	TPV	Demand allocation to suppliers							
		Region 1			Region 2			Region 3	
		sp_1^1	sp_1^2	sp_1^3	sp_2^1	sp_2^2	sp_2^3	sp_3^1	sp_3^2
176,707	−6.365	0.10093	0.14414	0.10039	0.11892	0.12137	0.13351	0.1153	0.10693
205,811	451.424	0.29842	0.10010	0.35963	0.14185	0.10000	0	0	0
184,691	118.699	0.23662	0.10000	0.15973	0.10065	0.10131	0.10019	0.1015	0.10000
187,748	335.015	0.25960	0.10664	0.15973	0.17165	0.10238	0.10000	0.10000	0
191,698	391.436	0.29824	0.10372	0.23153	0.14385	0.12266	0.10000	0	0
200,179	442.226	0.36731	0.11519	0.27611	0.14139	0.10000	0	0	0
201,486	448.923	0.37201	0.11339	0.31400	0.10060	0.10000	0	0	0
188,200	357.383	0.34610	0.13946	0.13336	0.12974	0.15136	0.10000	0	0
180,154	8.4060	0.24814	0.10000	0.10000	0.10000	0.10000	0.10000	0.10367	0.14819
180,513	46.5100	0.25848	0.10000	0.10000	0.10000	0.10000	0.10000	0.11166	0.12986
180,567	92.804	0.28350	0.10000	0.10000	0.10000	0.10000	0.10000	0.10467	0.11183
182,540	116.889	0.26026	0.10000	0.11418	0.12171	0.10303	0.10000	0.10059	0.10024
189,510	390.797	0.30602	0.10784	0.20978	0.17637	0.10000	0.10000	0	0
180,724	116.750	0.29233	0.10000	0.10000	0.10000	0.10000	0.10000	0.10656	0.10111
189,566	391.281	0.32141	0.11344	0.22539	0.13976	0.10000	0.10000	0	0
180,357	18.6814	0.24930	0.10320	0.10000	0.10000	0.10000	0.10000	0.10534	0.14215
180,238	17.0600	0.25036	0.10000	0.10000	0.10000	0.10000	0.10182	0.10379	0.14403

due to disruption, all suppliers are used and 37.38% of the total demand is assigned to the suppliers in Region 2 though the unit purchasing cost is higher than the Region 1 suppliers. The suppliers in Regions 1 and 3 are assigned 34.55% and 22.22% of the total demand respectively. In the minimum cost solution, the top 3 preferred suppliers are underutilized as more demand is assigned to suppliers sp_1^2, sp_2^3 and sp_2^2 resulting in a negative TPV. In the maximum TPV solution, 35.96% of the total demand is assigned to supplier sp_1^3 ranked second followed by supplier sp_1^1 who scored the highest preference value using the fuzzy PROMETHEE net flow.

With 50–80% of the total demand assigned to the top 3 preferred suppliers, TPV varies between 335.015 and 451.424. Table 9 shows that there are solutions in the non-dominated set which has a marked improvement in ETC with only a small reduction in TPV. Similarly, there are solutions in the non-dominated set, which have a large improvement in TPV with a slight increase in ETC. Fig. 6 shows the Pareto frontier of the MOPSO algorithm.

6.3. Sensitivity analysis

From the non-dominated solutions, two extreme solutions are selected and a sensitivity analysis is performed to study the effect of variations in failure probability, supply flexibility, and the loss cost of the suppliers on ETC.

Failure probability: The failure probability of the suppliers is varied at four levels while the other parameters presented in Table 4 are kept constant. The individual and combined effect of mis-estimating the failure probability of super event (p_{su}), semi-super event (p_{se}), and unique event (p_{uq}) on ETC are analyzed. Figs. 7a and 7b show that the combined effect of all the events yields a larger deviation in ETC. p_{uq} has more impact on ETC than the other two events. Larger deviations in ETC are observed when the error in estimating the failure probability is more than 50% in either direction. Further, underestimating the failure probability leads to a slightly larger deviation than over estimating the failure probability. In Fig. 7a, the deviation in ETC is less as compared to the deviation in Fig. 7b as more suppliers are selected for a minimum cost solution.

Supply flexibility: The supply flexibility index of the suppliers is varied at four levels while the other parameters reported in Table 4 are kept constant. The flexibility index of supplier sp_1^2 is unchanged as the value is set at 1. In the minimum cost solution of Fig. 8a, ETC is robust to changes in supply flexibility as demand is allocated to all suppliers to minimize the

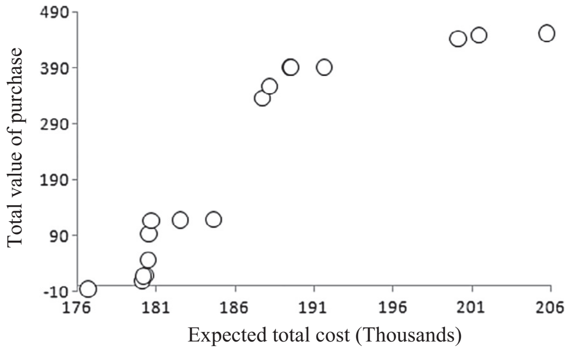

Fig. 6. Pareto frontier for illustrative example using MOPSO algorithm.

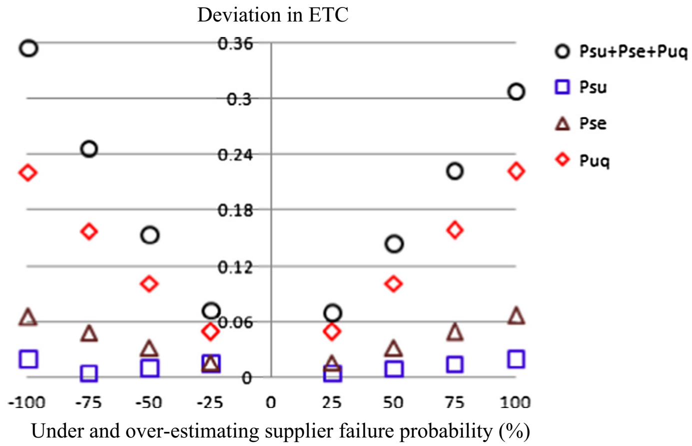

Fig. 7a. Effect of mis-estimating supplier failure probability on ETC for minimum cost.

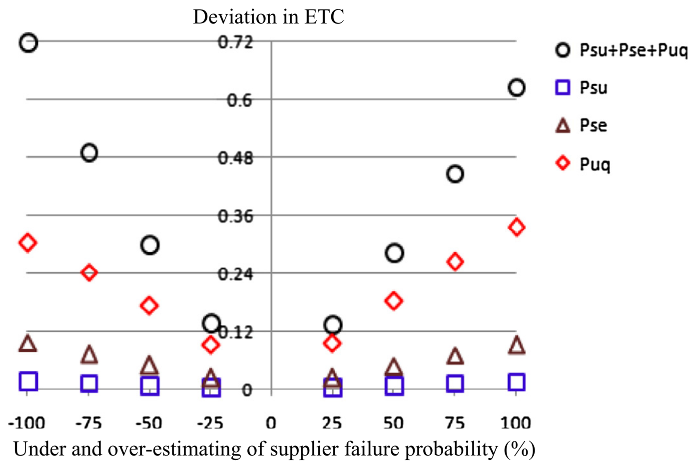

Fig. 7b. Effect of mis-estimating supplier failure probability on ETC for maximum TPV.

expected loss under disruption. The deviation in ETC is slightly higher in the maximum TPV solution as shown in Fig. 8b. Suppliers in Region 3 are not selected and hence the deviation in ETC is zero in the maximum TPV solution. The changes in the flexibility index of suppliers in Region 2 have slightly more impact on ETC, as compared to Regions 1 and 3. This is so as the failure probability of the suppliers in Region 1 is high and the capacity of the suppliers in Region 3 is low compared to those in Region 2.

Loss cost: The loss cost of the suppliers is varied at four levels while the other parameters reported in Table 4 are kept constant. In the minimum cost solution of Fig. 9a, the deviation in ETC increases when the loss cost of all the suppliers is increased. The suppliers from each Regions 1 and 2 are assigned nearly 35% of the demand and hence the deviation in ETC of both regions is almost the same. The deviation in ETC shown in Fig. 9b is slightly higher in the maximum TPV solution as the suppliers located in a single region are assigned nearly 75% of the demand. Suppliers in Region 3 are not selected and hence the deviation in ETC is zero in the maximum TPV solution. Thus, the increase in loss cost results in a higher deviation in ETC when the order is allocated to fewer suppliers.

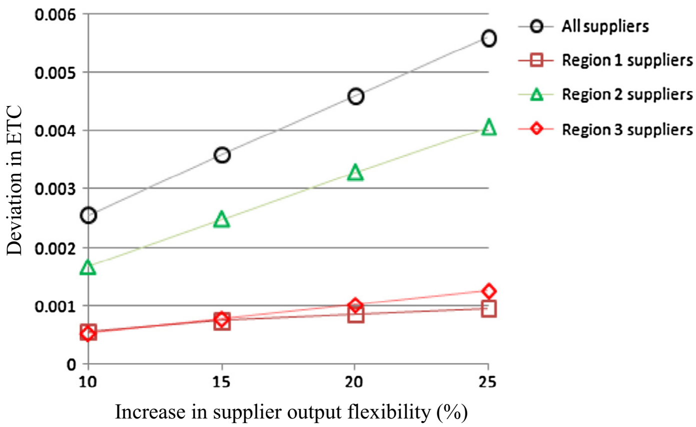

Fig. 8a. Effect of supplier output flexibility on ETC for minimum cost.

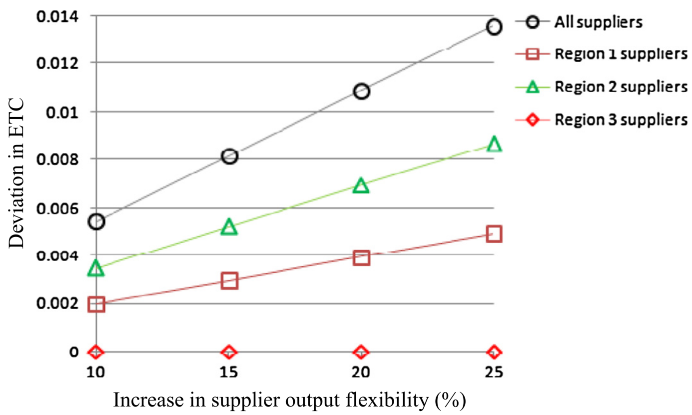

Fig. 8b. Effect of supplier output flexibility on ETC for maximum TPV.

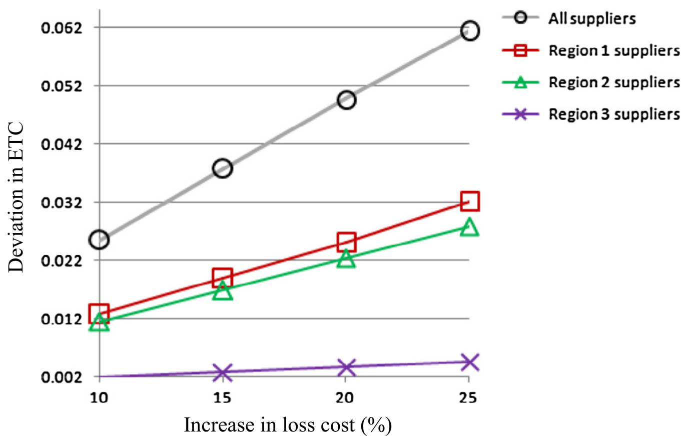

Fig. 9a. Effect of loss cost on ETC for minimum cost.

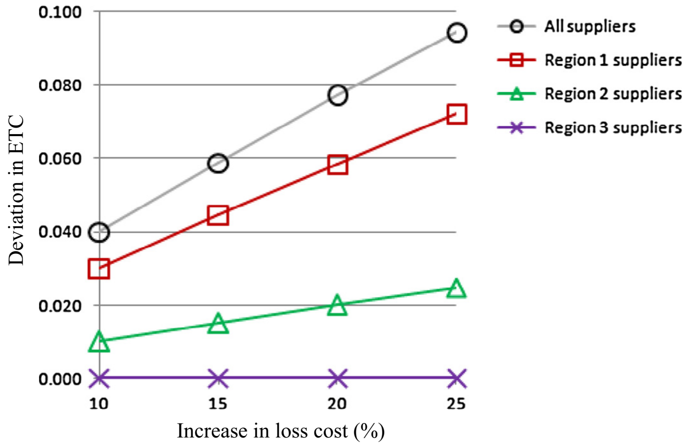

Fig. 9b. Effect of loss cost on ETC for maximum TPV.

7. Conclusion

We develop a multi-objective MILP model to determine the choice of suppliers and order quantity allocation under disruption risk. A two-phase solution approach is proposed where the suppliers are first ranked based on the preference value obtained using fuzzy AHP and fuzzy PROMETHEE. Then MOPSO is used to obtain a set of Pareto-optimal solutions with the choice of suppliers and order allocation among them. The results suggest that, to minimize the ETC, suppliers located in regions that are less prone to disruption are assigned more demand even though their preference value is smaller. This finding agrees with the results of Kamalahmadi and Mellat-Parast (2015). Similarly, to maximize the TPV, the suppliers located in a single region are assigned more demand considering their preference values which lead to higher ETC. Our numerical experiments suggest that the supplier failure probability affects ETC more than supplier flexibility and loss cost. The Pareto optimal solutions obtained enable us to evaluate a number of decision alternatives. A sensitivity analysis on the minimum ETC and maximum TPV solutions shows that the effect of mis-estimating the failure probability on ETC is less when more suppliers are chosen. ETC is also found to be less sensitive to the variation in the supply flexibility of the suppliers when multiple suppliers are selected. Keeping the other factors constant, an increase in loss cost results in a higher deviation in ETC when the order is allocated to a few suppliers.

In view of the present limitations of our model, such as deterministic demand, constant purchase price, zero supplier premiums for compensating the quantity loss, several extensions of this work are possible. Our model can be extended to include stochastic demands and discounts in the purchase cost. We have assumed that the undisrupted suppliers can compensate the shortfall at no extra cost. In practice, these suppliers may charge a premium to supply over the original allocation (Ruiz-Torres et al., 2013; Kamalahmadi and Mellat-Parast, 2015) and disrupted suppliers who fail to deliver the stipulated amounts may be penalized or be required to return a portion of the received purchasing cost. Other multi-objective meta heuristics could be developed to compare the results. A model for a multi-tier supply network considering multiple items with different shipment policies and for multiple periods considering the disruption duration can also be developed.

Acknowledgements

The first author acknowledges the National Institute of Technology, Tiruchirappalli-India for providing a travel grant to visit the second author under the Technical Education Quality Improvement Programme (TEQIP-II), during which this work was done. The authors thank the anonymous referees for their constructive comments.

Appendix A. Steps of fuzzy AHP

Step 1: Construct a fuzzy pair-wise comparison matrix using a decision maker's opinion. Consider the triangular fuzzy comparison matrix

$$\tilde{A}_{cxc} = \begin{bmatrix} (1,1,1) & \cdots & (l_{1,c}, m_{1,c}, u_{1,c}) \\ \cdots & \cdots & \cdots \\ (l_{c,1}, m_{c,1}, u_{c,1}) & \cdots & (1,1,1) \end{bmatrix}$$

Step 2: Defuzzify each triangular fuzzy number in the pair-wise comparison matrix using $\tilde{A}_{crisp} = (4 \otimes m + l + u)/6$. Compute the consistency index using the method in crisp AHP.

Step 3: Sum each row of the fuzzy pair-wise comparison matrix $\tilde{A}$ i.e.

$$\mathrm{RS}_i = \sum \tilde{a}_{ij} = \left(\sum_{j=1}^{c} l_{ij}, \sum_{j=1}^{c} m_{ij}, \sum_{j=1}^{c} lu_{ij}\right) \tag{A.1}$$

Step 4: Normalize the rows by the row sums

$$\widetilde{S}_i = \frac{RS_i}{\sum_{j=1}^{c} RS_j} = \left(\frac{\sum_{j=1}^{c} l_{ij}}{\sum_{j=1}^{c} l_{ij} + \sum_{k=1,k\neq i}^{c}\sum_{j=1}^{c} u_{kj}}, \frac{\sum_{j=1}^{c} m_{ij}}{\sum_{k=1}^{c}\sum_{j=1}^{c} m_{kj}}, \frac{\sum_{j=1}^{c} u_{ij}}{\sum_{j=1}^{c} u_{ij} + \sum_{k=1,k\neq i}^{c}\sum_{j=1}^{c} l_{kj}}\right), \quad i = 1, \ldots, c. \tag{A.2}$$

Step 5: Compute the degree of possibility of $\widetilde{s}_i \geqslant \widetilde{s}_j$

$$V(\widetilde{s}_i \geqslant \widetilde{s}_j) = \begin{cases} 1, & \text{if } \mathrm{m_i} \geqslant \mathrm{m_j} \\ \frac{\mathrm{u_i} - u_j}{(\mathrm{u_i} - m_i) + (\mathrm{m_j} - l_j)}, & \text{if } \mathrm{l_j} \leqslant \mathrm{u_i}, \quad \mathrm{i,j} = 1, \ldots n;\ j \neq i \\ 0, & \text{others} \end{cases} \tag{A.3}$$

Step 6: Calculate the degree of possibility of $\widetilde{S}_i$ over all other fuzzy numbers through

$$V(\widetilde{s}_i \geqslant \widetilde{s}_j | j = 1, \ldots, c; j \neq i) = \min_{\mathrm{j} \in \{1,\ldots,\mathrm{c}\}, \mathrm{j} \neq \mathrm{i}} V(\widetilde{s}_i \geqslant \widetilde{s}_j), \mathrm{i} = 1, \ldots, \mathrm{c}. \tag{A.4}$$

Step 7: Define the priority vector $W = (w_1, \ldots, w_c)^T$ of the fuzzy comparison matrix

$$w_i = \frac{V(\widetilde{s}_i \geqslant \widetilde{s}_j | j = 1, \ldots, c; j \neq i)}{\sum_{k=1}^{c} V(\widetilde{s}_k \geqslant \widetilde{s}_j | j = 1, \ldots, c; j \neq k)} \tag{A.5}$$

Appendix B. Steps of fuzzy PROMETHEE

Step 1: Construct the fuzzy evaluation matrix by comparing the alternatives based on each criterion using a suitable linguistic scale. The fuzzy PROMETHEE formulas are based on the representation of a triangular fuzzy number (TFN) as $x = (n, a, b)_{LR}$. In this notation, when the variable x has value n, it belongs to the specific class and its membership function is f(x) = 1. For values smaller than (n – a) and larger than (n + b), it does not belong to the specific class. In the interval [n – a < x < n + b], its membership degree is given by the membership function that varies between 0 and 1. L and R indicate the change of *f(x)* with *x* to the left and right of *n* respectively.

Step 2: Compare fuzzy numbers and compute the Yager index. The defuzzified form of the given fuzzy number is calculated by the function $F(n, a, b) = (3n - a + b)/3$. This process converts the fuzzy evaluation matrix into a crisp matrix.

Step 3: Apply preference functions with threshold for each criterion. Six types of preference functions are proposed in the literature, namely, uniform, U shape, V shape, level, linear and Gaussian (Tuzkaya et al., 2010). Let $P_j(a_1, a_2) = F_j[d_j(a_1, a_2)], \ \forall a_1, a_2 \in$ A be the preference function showing how much alternative 'a_1' is preferred to alternative 'a_2' with respect to criterion 'j' where $0 \leqslant P_j(a_1, a_2) \leqslant 1$.

Step 4: Compute the aggregated preference indices using $\prod(a_1, a_2) = \sum_{j=1}^{J} W_j P_j(a_1, a_2)$ where W_j denotes the weight associated with criteria 'j' and $0 \leqslant \prod(a_1, a_2) \leqslant 1$; $\prod(a_1, a_2)$ denotes the degree with which alternative 'a_1' is preferred over 'a_2' considering all criteria simultaneously.

Step 5: Calculate the outranking flows. The positive outranking flow expresses how alternative 'a' outranks all others and is computed using

$$\Phi^+(a) = \frac{1}{(A-1)} \sum_{x \in A} \prod(a, x) \tag{B.1}$$

A negative outranking flow represents how an alternative 'a' is outranked by all others and is computed using

$$\Phi^-(a) = \frac{1}{(A-1)} \sum_{x \in A} \prod(x, a). \tag{B.2}$$

All alternatives are completely ranked (PROMETHEE II) using the net flow which is computed from

$$\Phi(a) = \Phi^+(a) - \Phi^-(a). \tag{B.3}$$

References

Amin, S.H., Zhang, G., 2012. An integrated model for closed-loop supply chain configuration and supplier selection: multi-objective approach. Expert Syst. Appl. 39, 6782–6791.

Araz, C., Ozfirat, P.M., Ozkarahan, I., 2007. An integrated multi criteria decision making methodology for outsourcing management. Comput. Oper. Res. 34, 3738–3756.

Azadnia, A.H., Saman, M.Z.M., Wong, K.Y., 2015. Sustainable supplier selection and order lot-sizing: an integrated multi-objective decision making process. Int. J. Prod. Res. 53, 383–408.
Berger, P.D., Gerstenfeld, A., Zeng, A.Z., 2004. How many suppliers are best? A decision-analysis approach. Omega 32, 9–15.
Brans, J.P., Mareschal, B., 2005. PROMETHEE methods. In: Figueira, J., Greco, S., Ehrgott, M. (Eds.), Multiple Criteria Decision Analysis: State of the Art Surveys. Springer, pp. 163–196.
Chai, J., Liu, J.N.K., Ngai, E.W.T., 2013. Application of decision making techniques in supplier selection: a systematic literature review. Expert Syst. Appl. 40, 3872–3885.
Chang, D.Y., 1996. Applications of the extent analysis method on fuzzy AHP. Eur. J. Oper. Res. 95, 649–655.
Che, Z.H., 2012. A particle swarm optimization algorithm for solving unbalanced supply chain planning problems. Appl. Soft Comput. 12, 1279–1287.
Chen, S.H., 1985. Ranking fuzzy numbers with maximizing set and minimizing set. Fuzzy Sets Syst. 17, 113–129.
Chopra, S., Sodhi, M.S., 2014. Reducing the risk of supply chain disruptions. MIT Sloan Manage. Rev. 55, 73–80.
Deb, K., 2001. Multi-Objective Optimization Using Evolutionary Algorithms. John Wiley & Sons, New York.
Dubois, D., Prade, H., 1978. Operations on fuzzy numbers. Int. J. Syst. Sci. 9, 613–626.
Goumas, M., Lygerou, V., 2000. An extension of the PROMETHEE method for decision making in fuzzy environment: ranking of alternative energy exploitation projects. Eur. J. Oper. Res. 123, 606–613.
Hamdi, F., Ghorbel, A., Masmoudi, F., Dupont, L., 2015. Optimization of a supply portfolio in the context of supply chain risk management: literature review. J. Intell. Manuf. http://dx.doi.org/10.1007/s10845-015-1128-3.
Heckmann, I., Comes, T., Nickel, S., 2015. A critical review on supply chain risk – definition, measure and modeling. Omega 52, 119–132.
Ishizaka, A., Nguyen, N.H., 2013. Calibrated fuzzy AHP for current bank account selection. Expert Syst. Appl. 40, 3775–3783.
Jolai, F., Yazdian, S.A., Shahanaghi, K., Khojasteh, M.A., 2011. Integrating fuzzy TOPSIS and multi-period goal programming for purchasing multiple products from multiple suppliers. J. Purchasing Supply Manage. 17, 42–53.
Kamalahmadi, M., Mellat-Parast, M., 2015. Developing a resilient supply chain through supplier flexibility and reliability assessment. Int. J. Prod. Res. 54, 302–321.
Kamali, A., Fatemi Ghomi, S.M.T., Jolai, F., 2011. A multi-objective quantity discount and joint optimization model for coordination of a single-buyer multi-vendor supply chain. Comput. Math. Appl. 62, 3251–3269.
Kannan, D., Khodaverdi, R., Olfat, L., Jafarian, A., Diabat, A., 2013. Integrated fuzzy multi criteria decision making method and multi-objective programming approach for supplier selection and order allocation in a green supply chain. J. Cleaner Prod. 47, 355–367.
Khalili, S.M., Yazdani, M., Jolai, F., 2016. Supplier selection and order allocation planning under political and disruption risks. In: 12th International Conference on Industrial Engineering (ICIE).
Kilincci, O., Onal, S.A., 2011. Fuzzy AHP approach for supplier selection in a washing machine company. Expert Syst. Appl. 38, 9656–9664.
Knemeyer, A.M., Zinn, W., Eroglu, C., 2009. Proactive planning for catastrophic events in supply chains. J. Oper. Manage. 27, 141–153.
Lalwani, S., Singhal, S., Kumar, R., Gupta, N., 2013. A comprehensive survey: applications of multi-objective particle swarm optimization (MOPSO) algorithm. Trans. Combinator. 2, 39–101.
Lei, D.A., 2008. Pareto archive particle swarm optimization for multi-objective job shop scheduling. Comput. Ind. Eng. 54, 960–971.
Lee, A.H.I., 2009. A fuzzy supplier selection model with consideration of benefits, opportunities, costs and risks. Expert Syst. Appl. 36, 2879–2893.
Lee, S.H., 2015. Order allocation to cluster suppliers considering supply failure, multiple price discount, and supplier maintenance cost. J. Ind. Prod. Eng. 8, 528–537.
Li, Z., Wong, W.K., Kwong, C.K., 2013. An integrated model of material supplier selection and order allocation using fuzzy extended AHP and multi-objective programming. Math. Probl. Eng. Article ID 363718
Li, G., Zhang, L., Guan, X., Zheng, J., 2015. Impact of decision sequence on reliability enhancement with supply disruption risks. Transp. Res. Part E 90, 25–38.
Macharis, C., Springael, J., Brucker, K.D., Verbeke, A., 2004. PROMETHEE and AHP: the design of operational synergies in multi criteria analysis. Strengthening PROMETHEE with the ideas of AHP. Eur. J. Oper. Res. 153, 307–317.
Mafakheri, F., Breton, N., Goniem, A., 2011. Supplier selection-order allocation: a two stage multiple criteria dynamic programming approach. Int. J. Prod. Econ. 132, 52–57.
Marchese, K., Paramasivam, S., 2013. The Ripple Effects How Manufacturing and Retail Executives View the Growing Challenge of Supply Chain Risk Retrieved from <http://www2.deloitte.com/content/dam/Deloitte/global/Documents/Process-and-Operations/gx-operations-consulting-the-ripple-effect-041213.pdf>.
Meena, P.L., Sarmah, S.P., 2014. Mitigating the risks of supply disruption under stochastic demand. Int. J. Manage. Sci. Eng. Manage. 9, 157–168.
Meena, P.L., Sarmah, S.P., Sarkar, A., 2011. Sourcing decisions under risks of catastrophic event disruptions. Transp. Res. Part E 47, 1058–1074.
Meena, P.L., Sarmah, S.P., 2013. Multiple sourcing under supplier failure risk and quantity discount: a genetic algorithm approach. Transp. Res. Part E 50, 84–97.
Meena, P.L., Sarmah, S.P., 2016. Supplier selection and demand allocation under supply disruption risks. Int. J. Adv. Manuf. Technol. 83, 265–274.
Nooraie, S.V., Mellat-Parast, M., 2015. A multi-objective approach to supply chain risk management: integrating visibility with supply and demand risk. Int. J. Prod. Econ. 161, 192–200.
Nooraie, S.V., Mellat-Parast, M., 2016. Mitigating supply chain disruptions though the assessment of trade-offs among risks, costs and investment capabilities. Int. J. Prod. Econ. 171, 8–21.
Osiro, L., Lima-Junior, F.R., Carpinetti, L.C.R., 2014. A fuzzy logic approach to supplier evaluation for development. Int. J. Prod. Econ. 153, 95–112.
Poli, R., 2008. Analysis of the publications on the applications of particle swarm optimization. J. Artif. Evol. Appl. 8, 1–10.
PrasannaVenkatesan, S., Kumanan, S., 2012a. Multi-objective supply chain sourcing strategy design under risk using PSO and simulation. Int. J. Adv. Manuf. Technol. 61, 325–337.
PrasannaVenkatesan, S., Kumanan, S., 2012b. A multi-objective discrete particle swarm optimisation algorithm for supply chain network design. Int. J. Logist. Syst. Manage. 11, 375–406.
Ray, P., Jenamani, M., 2016. Sourcing decision under disruption risk with supply and demand uncertainty: a news vendor approach. Ann. Oper. Res. 237, 237–262.
Ruiz-Torres, A.J., Mahmoodi, F., 2006. A supplier allocation model considering delivery failure, maintenance and supplier cycle costs. Int. J. Prod. Econ. 103, 755–766.
Ruiz-Torres, A.J., Mahmoodi, F., 2007. The optimal number of suppliers considering the cost of individual supplier failures. Omega 35, 104–115.
Ruiz-Torres, A.J., Mahmoodi, F., Zeng, A.Z., 2013. Supplier selection model with contingency planning for supplier failures. Comput. Ind. Eng. 66, 374–382.
Saaty, T.L., 1990. How to make a decision: the analytic hierarchy process. Eur. J. Oper. Res. 48, 9–26.
Sawik, T., 2010. Single vs multiple objective supplier selection in a make to order environment. Omega 38, 203–212.
Sawik, T., 2014a. Joint supplier selection and scheduling of customer orders under disruption risks: single vs. dual sourcing. Omega 43, 83–95.
Sawik, T., 2014b. On the robust decision-making in a supply chain under disruption risks. Int. J. Prod. Res. 52, 6760–6781.
Sawik, T., 2014c. Optimization of cost and service level in the presence of supply chain disruption risks: single vs. multiple sourcing. Comput. Oper. Res. 51, 11–20.
Sawik, T., 2016. Integrated supply, production and distribution scheduling under disruption risks. Omega 62, 131–144.
Sarkar, A., Mohapatra, P.K.J., 2009. Determining the optimal size of supply base with the consideration of risks of supply disruptions. Int. J. Prod. Econ. 119, 122–135.
Shaw, K., Shankar, R., Yadav, S.S., Thakur, L.S., 2012. Supplier selection using fuzzy AHP and fuzzy multi-objective linear programming for developing low carbon supply chain. Expert Syst. Appl. 39, 8182–8192.

Tang, C.S., 2006. Perspectives in supply chain risk management. Int. J. Prod. Econ. 103, 451–488.
Torabi, S.A., Baghersad, M., Mansouri, S.A., 2015. Resilient supplier selection and order allocation under operational and disruption risks. Transp. Res. Part E 79, 22–48.
Tuzkaya, G., Gulsun, B., Kahaman, C., Ozgen, D., 2010. An integrated fuzzy multi-criteria decision making methodology for material handling equipment selection problem and an application. Expert Syst. Appl. 37, 2853–2863.
Viswanadham, N., Samvedi, A., 2013. Supplier selection based on supply chain ecosystem, performance and risk criteria. Int. J. Prod. Res. 51, 6484–6498.
Wang, Y.M., Luo, Y., Hua, Z., 2008. On the extent analysis method for fuzzy AHP and its applications. Eur. J. Oper. Res. 186, 735–747.
Yilmaz, B., Dağdeviren, M., 2011. A combined approach for equipment selection: F-PROMETHEE method and zero-one goal programming. Expert Syst. Appl. 38, 11641–11650.
Zeng, A.A., Berger, P.D., Gerstenfeld, A., 2005. Managing the supply side-risks in supply chains: taxonomies, processes and examples of decision making modeling. In: Geunes, J., Akcali, E., Pardalos, P.M., Romeijn, H.E., Shen, Z.J. (Eds.), Applications of Supply Chain Management and E-Commerce Research. Springer, pp. 141–160.
Zimmermann, H.J., 2010. Fuzzy set theory. Wiley Interdiscipl. Rev.: Comput. Stat. 2, 317–332.
Zouggari, A., Benyoucef, L., 2012. Simulation based fuzzy TOPSIS approach for group multi-criteria supplier selection problem. Eng. Appl. Artif. Intell. 25, 507–519.