A hybrid MCDM-FMOO approach for sustainable supplier selection and order allocation

Abstract

The growing interest in sustainability increases the challenges for decision makers in selecting the sustainable suppliers in which consider economic, environmental and social aspects. Particularly, decision makers are being increasingly motivated to improve their supply chain activities in coping efficiently with the objectives of sustainable development. Where the era of sustainability threatens the current supply chain partners to either cope with the new regulations of sustainability or leave the field for new players. Notwithstanding, most of the recent studies considered economic and green criteria in handling sustainable supplier selection and order allocation (SSS/OA) problems overlooking the social criteria which represents the third pillar of sustainability. This work aims at putting forward a hybrid Multi Criteria Decision-Making (MCDM)-Fuzzy Multi-Objective Optimization (FMOO) approach for a sustainable supplier selection and order allocation problem by considering economic, environmental and social criteria. Thus, an integrated Fuzzy AHP-Fuzzy TOPSIS is proposed to assess and rank suppliers according to three sets of criteria (i.e. conventional, green and social). A Multi-Objective Optimization Model (MOOM) is developed for choosing suppliers and allocating the optimal order quantities. To cope with the multiple uncertainties in the input data, the MOOM is reformulated into a Fuzzy Multi-Objective Optimization Model. The ε-constraint and LP-metrics approaches are used to reveal two sets of Pareto solutions based on the developed FMOO model. Finally, TOPSIS is applied to select the final Pareto solution that is closest to the ideal solution and furthest from the nadir solution. The effectiveness and the applicability of the developed hybrid MCDM-FMOO approach is demonstrated through a case study.

Keywords: Sustainability; Supplier selection and order allocation; Fuzzy sets; Multi-objective optimization; Multi criteria decision-making.

1. Introduction

Supply chains encompass different stages participated, directly or indirectly, in satisfying customers' demands. Graneshan and Harrison (1995) defined it as a network of facilities and distribution operations that performs the function of procurement of materials, transformation of these materials into intermediate and finished products, and the distribution of these finished products to customers. Douglas et al. (1998) defined it as the co-operation of companies to present merchandises to markets. Supply Chain Management: "*the systematic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purpose of improving the long-term performance of the individual companies and the supply chain as a whole*" (Mentzer et al., 2001). Büyüközkan and Çifçi (2011) defined supply chain management as all operations related to the flow of merchandises and services from the source point to the usage point. It mainly aims to plan, implement and control the supply chain network operations efficiently (Bhattacharya et al., 2010).

Supplier selection and order allocation is a main key factor in implementing a robust supply chain management (Mohammed et al., 2018 & 2017). This is based on the fact that firms depend more on suppliers to obtain a cost-effective product quality. Furthermore, purchasing activity is one of the main task for enterprises since its costs represents more than 50% of all enterprises 'internal costs (Mohammed et al., 2018b, c; and Yazdani et al., 2016). Supplier selection and order allocation can be defined as the activity of selecting the best suppliers and allocate the optimal quantity of products to be purchased among them for obtaining a stabilized environment of competitiveness (Mohammed et al., 2018a; and Rajesh and Ravi, 2015). Fundamentally, supplier selection can be divided into two types including (1) single-sourcing, one supplier can fulfil the entire enterprise's demands and decision makers need to make only one decision: which supplier is the best; and (2) multiple-sourcing which is the more common type, multiple suppliers need to be selected since no single supplier can fulfil all the enterprise's demands. However, multiple-sourcing is preferred since it affords guarantee of timely delivery and order flexibility due to the diversity of the firm's total orders (Jolai et al., 2011, Ferreira, D. Borenstein, 2012; and Chen, 2006). Generally, it is a major concern and a challenge for decision makers since several uncontrollable and unpredictable factors are involved (Bevilacqua et al., 2006). Where an impropriate selection may compromise financial and operational status of the enterprise (Mohammed et al., 2018a; and Faez et al., 2006). Thus, it is regarded as a complex, multi-criteria decision-making activity since different and conflicting criteria should be considered and assessed to assign consistent suppliers (Kannan et al., 2013). Kilic (2013) justified this complexity based on the changeable key-factors that may be uncertain and conflict with each other such as cost, delivery time, service level and product quality.

A sustainable supply chain management is a new pattern that has been emerging recently in industries and enterprises (Mohammed et al., 2018d, Nujoom et al., 2016). It makes a significant influence on supply chain performance in the economic, environmental and social aspects. Sustainable issues have become a mandatory part of the sustainable growth, which is one of the major concern for enterprises these days. The environmental issues have been addressed as a major issue at the recent United Nations Conference on the Sustainable Development (Fahimnia et al., 2015; Nujoom et al., 2017 & 2018). Besides, the growing interests in the sustainable growth increases the challenges for a decision maker in selecting the sustainable suppliers in which takin into account economic, environmental and social aspects. Where, decision makers are being increasingly motivated to improve their supply chain activities in coping efficiently with the objectives of sustainable development. Where the sustainable growth threatens the current supply chain partners to either cope with the new regulations or leave the field for new players. Arguably, sustainability of a supply chain depends mainly on the purchasing strategy of the supply chain partners. Thus, a sustainable supplier section and order allocation solution is a vital activity for successfully facing today's competitive business.

Within this boundary, the objectives of this study are as follows:

- Address the main economic, environmental and social criteria for sustainable supplier selection and order allocation
- Present a development of an approach to select the sustainable suppliers and to allocate the optimal quantity of products to be purchased from each selected supplier
- To assign relative importance weights of sustainable criteria
- To put forward managerial and practical implications of the study

This work contributes to the literature in developing a Hybrid Multi-Criteria Decision Making -Fuzzy Multi-Objective Optimization approach in relation to the supplier selection and order allocation problem with consideration of sustainable practices (traditional, green and social) for a metal factory in Saudi Arabia. Fuzzy Analytical Hierarchy Process (AHP) is used to assign the economic criteria, environmental criteria and social criteria. Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used to rank the suppliers with respect to these criteria. The determined weight is then used into a developed fuzzy multi-objective model to allocate the optimal quantity of products to be purchased from each selected supplier. This supports decision makers' evaluation regarding suppliers' performance in which the order allocation plan is set considering suppliers' sustainable performance. The ε-constraint approach and LP-metrics approach are used to reveal two sets of Pareto solutions based on the developed fuzzy multi-objective model. Finally, TOPSIS is employed to select the final Pareto solution based on solution quality that is closest to the ideal solution and furthest from the nadir solution (the worst possible solution). The researchers were actively engaged in the industrial setting, and, as a result, managers have gained better understanding what is meant by sustainability for their facility in their country. The problem formulation, the technique and application of the approach in empirical setting does not always require extremely complex formulation and solution techniques and presented approach can be easily adapted by the managers. It is expected that the developed hybrid approach can be used as an aid in supporting decision makers to effectively analyse and select the best sustainable supplier under multiple uncertainties.

Based on the reviewed literature as outlined in section2, the previous research works have concentrated only on the efficient performance of suppliers from an economic and environmental perspective overlooking the social efficiency (Mahdiloo et al., 2015; Anisul Huq et al., 2014; and Grimm et al., 2016). Where very limited studies have considered economic, environmental and social criteria simultaneously in solving supplier selection and order allocation problem using MCDM algorithms and mathematical optimization models. In other word, the concentration on sustainability aspect in supplier selection and order allocation problem is at an early stage. To the best of our knowledge, this study is original in the sense that it integrates Fuzzy AHP, Fuzzy TOPSIS and TOPSIS with a fuzzy multi-objective optimization model to solve a sustainable supplier selection and order allocation problem considering the three pillars of sustainability.

The rest of this article is presented as follows: Section 2 reviews the previous literature on supplier selection criteria and mathematical programming approaches applied for solving supplier selection and order allocation problems. Section 3 presents a development of the hybrid MCDM-FMOO approach. Section 4 presents a case study, results and discussions. Section 5 highlights managerial and practical implication of this study. Sections 6 concludes the work and provides avenues for future research.

2. Literature review

In this work, the literature review is presented into two sections. First, the supplier relationship management (SRM) is discussed. Second, the criteria used in assessing and ranking suppliers are highlighted. Third, MCDM and mathematical programming approaches used for solving supplier selection and order allocation problems are reviewed.

2.1 Supplier Relationship Management:

In order to manage the collaboration and relationship between the supply chain actors among the supply chain management, supplier relationship management was introduced. Since from the Kraljic model (1983), the supplier relationship management is evolved and the most acclaimed definition given by the Sanders (2012) as "co-ordination, collaboration and information sharing between supply chain members". After the introduction of Lamming (1993) model, the customer-supplier relationship model gets developed with various approach of researches. These different perspectives of analyzing the SRM leads to many literature over different applications. For an instance, Forkmann et al (2016) and Tseng (2014) analyzed the relationship between the SRM capability and firm's business performance; however, this study identified the qualification and extension of SRM capabilities. Some studies (Oghazi et al 2016) examined the effective SRM process between the focal companies and their corresponding different tier suppliers. Likewise, many conceptual perspectives of SRM has been analyzed over years which includes importance (Teller et al., 2016), frameworks and models (Ibrahim and Moertini, 2015; Park et al., 2010), Visibility (Fan et al., 2013), as a business (Lambert and Schwieterman, 2012), SRM policies and practices (Miocevic and Crnjak-Karanovic, 2012; Emiliani, 2010), risk and trust (Jiang et al., 2011), price behavior (Gyau et al., 2011), organizational design (Kaiser and Buxmann, 2017).

Though there are many studies exhibit the SRM with various concepts, but very few studies focused on anyone or all the sustainable dimensions. Tidy et al (2016) discussed the impact of SRM in the environmental sustainability through the reduction of greenhouse gas emissions in the application of UK food supply chains. From the review of literatures, it can be evident that most of the studies focused on the environmental sustainability in the relation with SRM. Very limited studies considered all three dimensions with the concern of SRM, for an instance, Leppelt et al (2013) investigated the effect of sustainable supplier relationship management (SSRM) on corporate image with the application of chemical industry. Eventually the previous studies fails to combines the sustainability and order allocation in supplier selection, which gives a room to explore further. With this concern, this study proposed a research framework with MCDM to select the supplier based on sustainability and order allocation.

2.2 Supplier selection criteria

Supplier selection and order allocation (SS/OA) is a multi-criteria issue in which choosing proper criteria is a main key factor in decision-making of supplier assessing and ranking (Büyüközkan and Çifçi 2011). Several researches have been presented taking into account various criteria for the supplier selection activity. Dickson (1966) highlighted 23 criteria for supplier selection through a survey of purchasing decision makers. The study ranked the criteria as quality/delivery/performance/history warranties/capacity and cost of production facilities. In a similar study, Weber et al. (1991) addressed that net price is a main key measure in decision making for supplier selection. Roa and Kiser (1980) and Bache et al. (1987) highlighted, respectively, 60 and 51 criteria for supplier selection. Ghodsypour and O'Brien (1998) presented an analysis of criteria talking into account for supplier selection. The results demonstrated that the purchasing strategies allocate the criteria and their relevant importance weights. Ho et al. (2010) argued that the most popular supplier selection criteria are obtained as quality, delivery and price. Chang et al. (2011) performed a study for highlighting the top 10 criteria that received most attention in the literature. The criteria are cost, delivery reliability, lead time, flexibility, quality, capacity of related facilities, production and technology capability, reduction on demand change, environmental control and service level. Consequently, the selection criteria are not the same in all studies.

Sustainability concerns have been increasingly growing among stakeholders and academics (Amindoust et al. 2012). Thus, sustainability criteria are being increasingly considered in SS/OA problems. Sustainable SCM could be defined as the management of operation, information flow and cash flow, throughout the supply chain considering three targets in terms of three dimensions which include economic, environmental and social based on the requirement of decision makers and customers. The studies on sustainable supplier ranking using social criteria considerations are quite limited. Based on the reviewed literature, the main social criteria are collected as staff development, safety, rights and health of employees and information disclosure.

2.3 MCDM and mathematical programming approaches in supplier selection

As mentioned previously, SS/OA is a multi-objective decision-making problem and several MCDM and mathematical programming approaches have been employed to handle the problem in the literature (Vanteddu et al., 2011; Mafakheri et al., 2011; Lin, 2012; Ekici, 2013; Qian, 2014; Karsak and Dursun, 2015; Deng et al., 2014; Prakash and Barua, 2016; Senthil et al., 2014; Mohammed and Wang, 2015 and Sivrikaya et al., 2015). Chai et al. (2013) presented a literature review of MCDM approaches used for supplier selection according to the published works from 2008 to 2012. Their work addressed 26 approaches defined into three main classifications: (i) Mathematical programming approaches such as linear programming, nonlinear programming, multi-objective programming, goal programming and stochastic programming; (ii) MCDM approaches such as TOPSIS, ELECTRE, AHP and ANP and; (iii) Artificial intelligence approaches such as genetic algorithm and neural network. However, their study highlighted that most commonly used approaches are AHP, TOPSIS and multi-objective programming. This was also supported by a study presented by Govindan et al. (2015); and Fallahpour and Moghassem (2012). With regards to AHP, the decision makers have the ability to incorporate qualitative and quantitative criteria in the unified evaluation framework.

Awasthi et al. (2010) used Fuzzy TOPSIS algorithm for solving a supplier selection problem considering the environmental performance. Shaw et al. (2012) proposed an integrated fuzzy-AHP and fuzzy multi-objective linear programming for solving a supplier selection problem taking into account greenhouse gas emission, cost, quality, lead time and demand criteria for evaluating and ranking suppliers. Magdalena (2012) proposed an approach to select the best supplier in a food industry using Taguchi Loss Function and Fuzzy AHP. Amorim et al. (2016) proposed an integrated framework for solving supplier selection problem in the processed food industry. A multi-objective model was developed to simultaneously optimize the minimization of risk of low customer service and maximization of profit. Kannan et al. (2015) investigated a green supplier selection problem in a plastic enterprise using a fuzzy axiomatic design approach. Govindan and Sivakumar (2016) used an integrated multi-criteria decision making and multi-objective linear programming approaches as an aid to select the best green supplier. Trapp and Sarkis (2016) presented a programming model that concurrently considered supplier selection with respect to sustainability concerns. Similar studies have been carried out in the past considering environmental criteria in ranking the suppliers (Amindoust et al., 2012; Hashemi et al., 2015; Awasthi and Kannan, 2016; Rezaei et al., 2016; and Luthra et al., 2017).

In the context of SSS/OA considering the three pillars of sustainability, very little study has been conducted (Mahdiloo et al., 2015; and Govindan et al., 2017). Bai and Sarkis (2010) assessed supplier selection decisions by incorporating sustainability factors in their optimization model. Punniyamoorthy et al. (2011) based on safety and social environmental criteria for supplier ranking through a development of a structural equation modelling and Fuzzy AHP approach. Amindoust et al. (2012) rated suppliers in a sustainable supply chain context. Their study did not consider all applicable sub-criteria to sustainable supplier selection. Azadnia et al. (2012) proposed an integrated self-organizing map and MCDM approach for a solving supplier selection problem. Their study considered economic, environmental and social criteria in terms of occupational health and safety management systems and the rights of stakeholders. Govindan et al. (2013) proposed a Fuzzy TOPSIS approach for rating suppliers based on their performance regarding sustainability criteria. Luthra et al. (2017) employed AHP and VIKOR approaches for analyzing and ranking the sustainable suppliers in a supply chain.

The paper presents a fuzzy Multi-Objective Optimization Model that is developed for choosing suppliers and allocating the optimal order quantities by considering economic, environmental and social criteria. The multi-objective model was transformed to a fuzzy multi-objective model to consider the dynamic nature of some input parameters (for example, costs, demands, CO_2 emissions and capacity levels). The fuzzy set theory is used when there are imprecise and vague information, for example when using judgment of decision makers. In fuzzy logic, the uncertainties of fuzzy sets are characterized through an establishment of membership functions.

3. Developing the hybrid MCDM-FMOO approach

Fig. 1 illustrates the supply chain under study which consists of suppliers, a factory and markets. This research aims at supporting decision makers in selecting the best sustainable suppliers and the optimal quantity of products to be ordered from each supplier according to their performance in conventional (e.g. purchasing cost, delivery time and reliability), environmental and social aspects. To this end, a hybrid MCDM-FMOO approaches is developed as follows:

1. A unified framework that identifies conventional, green and social criteria is developed. This could be derived from the literature and decision makers ‘expert.
2. Fuzzy AHP is used for assigning relative weights of sustainable selection criteria based on expert’s assessment.
3. Fuzzy TOPSIS is used for assessing suppliers based on their sustainable performance, and subsequently, the ranking order of suppliers was determined.
4. If decision makers are satisfied with suppliers’ sustainable performance, the obtained relative weights of sustainable criteria and suppliers are then integrated into a developed multi-objective model that aims at minimizing the expected cost, and environmental impact and maximizing social impact and total purchasing value. The satisfaction

margin of decision makers regarding suppliers' 'sustainable performance will be explained in section 3.3 later.

5. To cope with the dynamic nature of some of the input parameters (i.e., costs, demands, CO_2 emissions and capacity levels), the multi-objective model is transformed to a fuzzy multi-objective model.
6. Two different solution approaches (i.e., ε-constraint and LP-metrics) are used to solve the multi-objective optimization model in terms of obtaining Pareto solutions.
7. Finally, TOPSIS is used to rank the obtained Pareto solutions based on their closeness from the ideal solution. This helps the decision makers in selecting the final solution in determining the optimal order allocation.

Fig. 2 illustrates the main procedures of the developed hybrid MCDM-FMOO approach for solving a sustainable supplier selection and order allocation problem.

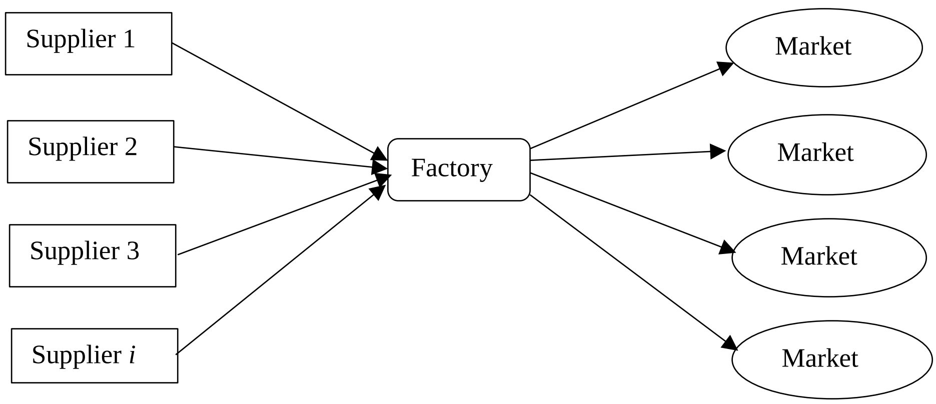


Fig. 1. The supply chain under study.

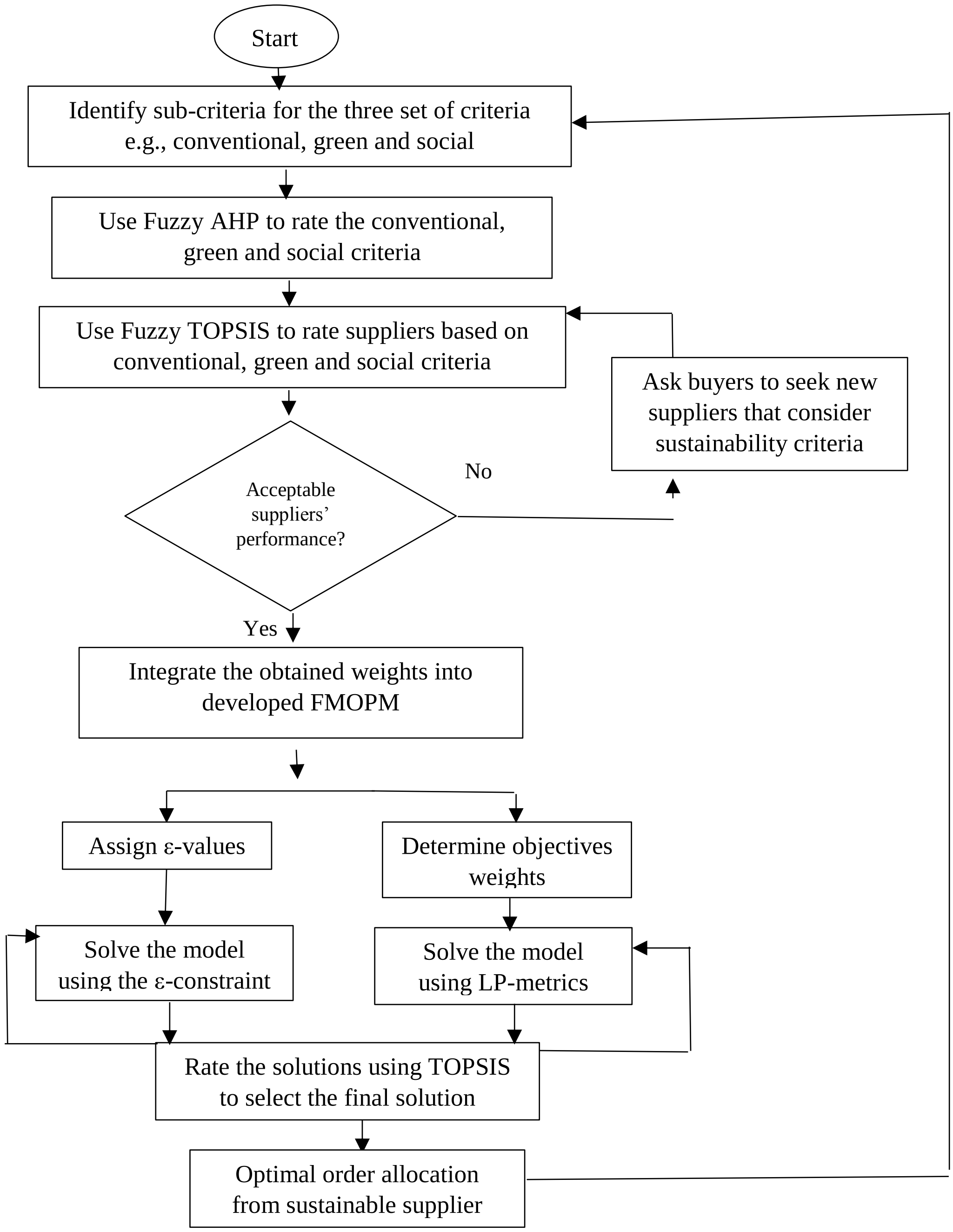


Fig. 2. Flow chart of the developed hybrid MCDM-FMOO approach.

3.1 Fuzzy set theory

In really, many input data such as cost and potential market demands are normally varied. Therefore, issues of uncertainty need also to be considered in activities of supply chain management (Fattahi et al., 2015). Fuzzy logic is one of the main approach that is used to come closer to reality. Several researchers applied fuzzy methods to tackle the fuzziness as input data of supply chain management (Qin & Ji, 2010; Gholamiana et al., 2015). Initially, Fuzzy set theory was initially introduced by Zadeh (1965) for modelling and analysing uncertain and vague data. In fuzzy logic, the uncertainties of fuzzy sets are characterized through an establishment of membership functions. The membership function values are varied between 0 and 1. The membership value 1 means that the elements are in the central of the fuzzy set. The membership value 0 means that element outside the fuzzy set. The membership value between 0 and 1 means the elements construct the frontier of the fuzzy set.

3.2 Ranking the criteria: Fuzzy AHP

Fuzzy AHP is a decision-making algorithm presented by incorporating Saaty's (Saaty, 2000). AHP developed in the 1970s with fuzzy set theory (Zimmermann, 2010). In this algorithm, fuzzy numbers are presented by a membership function that is a real number between 0 and 1. Several research works have proved its applicability in solving supplier selection problem (Lee, 2009; Kilincci and Onal, 2011; Kannan et al., 2013; Viswanadham and Samvedi, 2013; and Junior et al., 2014). In this work, Fuzzy AHP is used for assigning importance weights for each sub-criterion for each of the three criteria (i.e. conventional, green and social). Table 1 presents the linguistic variables used for weighting the criteria (Lau et al., 2003). For example, the linguistic evaluation ''strongly more important (SMI)'' corresponds to the numerical evaluation (0.3, 0.5, 0.7). Decision makers need to assign an importance level to every sub-criterion in each of the three sets of criteria based on their experts. The Fuzzy AHP implementation is presented into slight different steps in the literature mentioned previously. In this work, the procedures followed by Wang et al.'s (2008) are employed.

1. Use a decision maker's preference to build a fuzzy pair-wise comparison matrix:

$$\tilde{A} = \begin{bmatrix} (1,1,1) & \ldots(a_{1j}, n_{1j}, m_{1j}) & \\ \ldots & \ldots & \ldots \\ (a_{i1}, n_{i1}, m_{i1}) & \ldots & (1,1,1) \end{bmatrix}; \; i = 1, 2, 3, \ldots, I; \; j = 1, 2, 3, \ldots, J$$

where I and J refers to the criteria to perform the pairwise comparison among them.

2. Transform each fuzzy number in the matrix using

$$A_{crisp} = \frac{(4 \otimes a + n + m)}{6} \tag{1}$$

Where a, n and m correspond to the fuzzy number presented in Table 1.

3. Use the approach in crisp AHP to determine the consistency index.
4. Sum each row of the $\tilde{A}$ as follows:

$$RowS_i = \left(\sum_{j \in J} a_{ij}, \sum_{j \in J} n_{ij}, \sum_{j \in J} m_{ij} \right); \quad i = 1, 2, 3, ..., I \tag{2}$$

5. Normalize the rows by the row sums as follows:

$$\tilde{S}_i = \frac{RowS_i}{\sum_{j \in J} RowS_i} = \left(\frac{\sum_{j \in J} a_{ij}}{\sum_{j \in J} a_{ij} + \sum_{j \in J} m_{ij}}, \frac{\sum_{j \in J} n_{ij}}{\sum_{j \in J} n_{ij}}, \frac{\sum_{j \in J} m_{ij}}{\sum_{j \in J} m_{ij} + \sum_{j \in J} a_{ij}} \right), \quad i = 1, ..., I \tag{3}$$

6. Determine the degree of possibility of $\tilde{S}_i \geq \tilde{S}_j$

$$V(\tilde{S}_i \geq \tilde{S}_j) = \begin{cases} 1 & if \ \mathrm{n}_i \geq n_j \\ \dfrac{m_i\text{-}a_j}{(n_i - m_j) + (n_i - a_i)} & if \ \mathrm{a}_j \leq m_j; \ i = 1...I, \ j = 1...J; \ j \neq i \\ 0 & others \end{cases} \tag{4}$$

7. Determine the degree of possibility of $\tilde{S}_i$ over all other fuzzy numbers as follows:

$$V(\tilde{S}_i \geq \tilde{S}_j \mid j = 1, ..., J, i \neq j) = \min_{j \in \{1,...,J\}, j \neq j} V(\tilde{S}_i \geq \tilde{S}_j), i = 1, ..., I \tag{5}$$

8. Construct the priority vector $W = \left(w_1, ..., w_j\right)$ of the fuzzy comparison matrix as follows:

$$w_i = \frac{V(\tilde{S}_i \geq \tilde{S}_j \mid j = 1, ..., J, \ j \neq i)}{\sum_{k \in c} V(\tilde{S}_k \geq \tilde{S}_j \mid j = 1, ..., J, \ j \neq k)}, i = 1, ..., I \tag{6}$$

Table 1. Linguistic variables for ranking criteria and sub-criteria

Linguistic Variable	Fuzzy number (*a*, *n*, *m*)
Equally important (EI)	(0, 0.1, 0.3)
Weakly important (WI)	(0.1, 0.3, 0.5)
Strongly more important (SMI)	(0.3, 0.5, 0.7)
Very strongly important (VSI)	(0.5, 0.7, 0.9)
Extremely important (EI)	(0.7, 0.9, 0.10)

3.3 Ranking the suppliers: Fuzzy TOPSIS

TOPSIS is firstly proposed by Hwang and Yoon (1981) and has been applied a lot since then. This approach can be used for selecting a solution nearest to the ideal solution, but also the farthest from the negative ideal solution. However, there is an argument on the insufficiency of it in coping with the dynamic nature of decision makers ‘preferences. Thus, TOPSOS is extended to Fuzzy TOPSIS to overcome this problem (Chen, 2000). In this work, Fuzzy TOPSIS is used for ranking of the suppliers based on conventional criteria, green criteria and sustainable criteria. Table 2 presents the linguistic variables used for ranking the alternatives considering each criterion (Lau et al., 2003). For example, the linguistic evaluation ‘‘High (H)’’ corresponds to the numerical evaluation (5, 7, 9). Decision makers need to evaluate suppliers with respect to each criterion in each of the three criteria (e.g. conventional, green and social). Fuzzy TOPSIS is implemented as follows (Mohammed et al., 2018):

Eq. (7) is used to normalize the fuzzy decision table to get the normalized decision table (Wang, 2014):

$$\tilde{R} = \begin{bmatrix} (1,1,1) & \dots & (a_{1j}, n_{1j}, m_{1j}) \\ \dots & \dots & \dots \\ (a_{i1}, n_{i1}, m_{i1}) & \dots & (1,1,1) \end{bmatrix}; \; i = 1, 2, 3, \dots, I; \; j = 1, 2, 3, \dots, J \tag{7}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{\sqrt{\sum_i m_{ij}^2}}, \frac{n_{ij}}{\sqrt{\sum_i m_{ij}^2}}, \frac{m_{ij}}{\sqrt{\sum_i m_{ij}^2}} \right) \tag{8}$$

where $\tilde{r}_{ij}$ is the normalized value of each element in matrix $\tilde{R}$. *a*, *n* and *m* correspond to the fuzzy number presented in Table 2. Also, *I* refers to the number of suppliers and *J* refers to the number of criteria.

The weights of criteria ($\tilde{W}$) need to be multiplied by the elements of the normalized decision table ($\tilde{R}$) to form weighted normalized decision matrix ($\tilde{V}$).

$$\tilde{V} = \left[\tilde{v}_{ij} \right]_{IxJ} \tag{9}$$

Where $\tilde{v}_{ij}$ is obtained using the following equation:

$$\tilde{v}_{ij} = \tilde{r}_{ij} \text{ x } \tilde{w}_j \tag{10}$$

The fuzzy positive ($\tilde{A}^+$) and negative ($\tilde{A}^-$) ideal solutions are determined using Eq. 11 and 12, respectively.

$$\tilde{A}^+ = \left\{ \tilde{v}_1^+, \tilde{v}_2^+, ..., \tilde{v}_i^+ \right\} \tag{11}$$

$$\tilde{A}^- = \left\{ \tilde{v}_1^-, \tilde{v}_2^-, ..., \tilde{v}_i^- \right\} \tag{12}$$

The distance of supplier "*i*" from the fuzzy positive ideal solution (d_i^+) and the fuzzy negative ideal solution (d_i^-) are calculated as follows:

$$d_i^+ = \sum_{j \in n} d_v \left(\tilde{v}_{ij}, \tilde{v}_j^+ \right); \; d_i^- = \sum_{j \in n} d_v \left(\tilde{v}_{ij}, \tilde{v}_j^- \right); \tag{13}$$

Where v_j^+ and v_j^- are fuzzy positive ideal point and fuzzy negative ideal point for the criterion "*j*", respectively.

Based on d_i^+ and d_i^-, the fuzzy closeness coefficient (*CC*) for each supplier is then determined using Eq. 14. The supplier with the highest *CC* (varies between 0 and 1) is selected as the best alternative.

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, ..., I \tag{14}$$

In this research, it is worthy to mention that, the minimum acceptable *cc* is set to be 0.5 in which a supplier that reveal a *cc* of less than 0.5, it will be eliminated, and so, no raw material order will be assigned. However, other satisfaction margin can be set based on decision makers 'preferences.

Table 2. Linguistic variables for ranking suppliers

Linguistic Variable	Fuzzy number (*a*, *n*, *m*)
Very Low (VL)	(0, 1, 3)
Low (L)	(1, 3, 5)
Medium (M)	(3, 5, 7)
High (H)	(5, 7, 9)
Very High (VH)	(7, 9, 10)

3.4 Formulating the multi-objective optimization model

In this work, a multi-objective programming model is developed to allocate the optimal number of products to be ordered from each supplier with respect to the sustainable criteria. The objectives are minimization of the expected costs (Z_1), minimization of environmental impact (Z_2), maximization of social impact (Z_3) and maximization of total purchasing value (Z_4).

Set

I set of suppliers $(1\ldots\ i\ldots\ I)$

Parameter

C_i^p purchasing cost per unit of product ordered from supplier *i*

C_i^t unit transportation cost per mile from supplier *i*

C_i^a administration cost per order of supplier *i*

d_i transportation distance (mile) of product from supplier *i*

TC transportation capacity (units) per lorry

S_i maximum supply capacity (units) of supplier *i*

D_i minimum quantity (units) of product to be ordered from supplier *i*

CO_{2i} CO_2 emission in gram per mile for each lorry travelling from supplier *i*

CW Weight of the conventional set of criteria obtained from Fuzzy AHP

GW Weight of the set of green criteria obtained from Fuzzy AHP

SW Weight of the set of social criteria obtained from Fuzzy AHP

w_i^c Closeness coefficient of supplier *i* obtained from Fuzzy TOPSIS with respect to the conventional criteria under consideration

w_i^g Closeness coefficient of supplier *i* obtained from Fuzzy TOPSIS with respect to the green criteria under consideration

w_i^s Closeness coefficient of supplier *i* obtained from Fuzzy TOPSIS with respect to the social criteria under consideration

Decision variables

q_i quantity of products ordered from supplier *i*

Binary decision variables

$$u_i = \begin{cases} 1\text{: if supplier } i \text{ is selected} \\ 0\text{: otherwise} \end{cases}$$

Based on the aforementioned notations, the four objective functions are formulated as follows:

$$Min\ Z_1 = \sum_{i \in I} C_i^p q_i + \sum_{i \in I} C_i^a u_i + \sum_{i \in I} C_i^t \left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{15}$$

$$Min\ Z_2 = \sum_{i \in I} CO_{2i} \left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{16}$$

$$Max\ Z_3 = \sum_{i \in I} w_i^s q_i \tag{17}$$

$$Max\ Z_4 = CW \left(\sum_{i \in I} w_i^c q_i \right) + GW \left(\sum_{i \in I} w_i^g q_i \right) + \mathrm{S}W \left(\sum_{i \in I} w_i^s q_i \right) \tag{18}$$

Eq. 15. aims at minimizing the sum of purchasing cost, administration cost (e.g. ordering and documentation) and transportation cost. Eq. 16. aims at minimizing the environmental impact in terms of CO_2 emissions throughout the transportation process. Eq. 17 aims at maximizing the social impact of suppliers. To this aim, Suppliers' weights in social criteria obtained by Fuzzy AHP are employed as a coefficient for all products ordered from supplier *i*. Eq. 18 aims at maximizing the total purchasing value considering conventional, green and social aspects. To this aim, the criteria weights obtained from Fuzzy AHP are multiplied by the weights of alternatives obtained from Fuzzy TOPSIS; to reflect the impact of the products ordered on the performance of factory, they are then multiplied by all products to be ordered from supplier *i*.

Subject to:

Supply capacity constraints

These constraints ensure that all quantity of product ordered from supplier *i* should be equal to or less than the capacity of supplier *i* (Mohammed et al., 2017*)*. It can be formulated as follows:

$$\sum_{i \in I} q_i \le S_i u_i \tag{19}$$

Demand constraints

These constraints ensure that the demands of the factory are fulfilled from supplier *i*. It can be formulated as follows:

$$\sum_{i \in I} q_i \ge \mathrm{D}_i \tag{20}$$

Non-negativity and binary constraints

These constraints ensure that the quantity of all products throughout the supply chain are non-negative (eq. 21); and the decision variables u_i is binary (Eq.22). They can be formulated as follows:

$$q_i \ge 0 \quad \forall i \tag{21}$$

$$u_i \in \{1, 0\}, \quad \forall i \tag{22}$$

3.4.1 Formulating the FMOO model

As mentioned previously, several input parameters are subject to uncertainty in the real world. In this study, to cope with the dynamic nature of the input data in transportation and purchasing costs, demands, CO_2 emissions and capacity levels, the multi-objective optimization model formulated in section 3.4 was re-formulated in FMOO model. The equivalent crisp model can be expressed as follows (Jiménez et al., 2007; Mohammed and Wang, 2016 and 2017):

Parameters

α satisfaction level of the fuzzy number, ($0 \le \alpha \le 1$)
mos the most likely value
pes the most pessimistic value

opt the most optimistic values

$$Min\ Z_1 = \sum_{i \in I} \left(\frac{C_i^{p\,pes} + 2C_i^{p\,mos} + C_i^{p\,opt}}{4} \right) q_i \ + \tag{23}$$

$$+ \sum_{i \in I} C_i^a u_i \ + \sum_{i \in I} \left(\frac{C_i^{t\,pes} + 2C_i^{t\,mos} + C_i^{t\,opt}}{4} \right) \left\lceil \frac{q_i}{TC} \right\rceil d_i$$

$$Min\ Z_2 = \sum_{i \in I} \left(\frac{CO_{2i}^{\ pes} + 2CO_{2i}^{\ mos} + CO_{2i}^{\ opt}}{4} \right) \left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{24}$$

$$Max\ Z_3 = \sum_{i \in I} w_i^s q_i \tag{25}$$

$$Max\ Z_4 = CW \left(\sum_{i \in I} w_i^c q_i \right) + GW \left(\sum_{i \in I} w_i^g q_i \right) + \mathrm{S}W \left(\sum_{i \in I} w_i^s q_i \right) \tag{26}$$

Subject to

$$\sum_{i \in I} q_i \ \le S_i \left[\frac{\alpha}{2} . \frac{S_{i\,1} + S_{i\,2}}{2} + \left(1 - \frac{\alpha}{2} \right) \frac{S_{i\,3} + S_{i\,4}}{2} \right] u_i \tag{27}$$

$$\sum_{i \in I} q_i \ \ge \left[\frac{\alpha}{2} . \frac{D_{i1} + D_{i2}}{2} + \left(1 - \frac{\alpha}{2} \right) \frac{D_{i3} + D_{i4}}{2} \right] \tag{28}$$

$$q_i \quad \ge 0 \quad \forall i \tag{29}$$

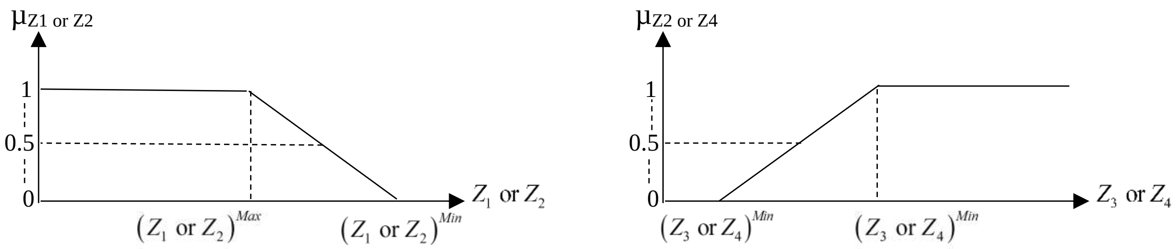
$$u_i \ \in \{1, 0\}, \quad \forall i \tag{30}$$

Based on this fuzzy formulation, the constraints in the FMOO model should be satisfied with a confidence value which is denoted as α and it is normally determined by decision makers. The α value is associated with the uncertain parameters which include transportation and purchasing costs, demands, CO_2 emissions and capacity levels. Also, mos, pes and opt are the three prominent points (the most likely, the most pessimistic and the most optimistic values), respectively (Jiménez et al., 2007; Dukyil et al., 2017, 2018).

Each objective function (Eq. 23-26) corresponds to an equivalent linear membership function, which can be determined by using Eq. 31. Fig.3 shows further illustration about these membership functions for each objective.

$$\mu_b = \begin{cases} 1 & if \;\; A_b \le Max_b \\ \dfrac{Max_b - A_b}{Max_b - Min_b} & if \;\; Min_b \le A_b \le Max_b \\ 0 & if \;\; A_b \ge Min_b \end{cases} \tag{31}$$

where A_b represents the value of b^{th} objective function and Max_b and Min_b represent the maximum and minimum values of b^{th} objective function, respectably.



(a) Z_1 and Z_2 (b) Z_3 and Z_4

Fig. 3. Illustration of membership functions of the four objectives (a) Z_1 and Z_2, (b) Z_3 and Z_4.

The minimum and maximum values (Max, Min) for each objective function can be obtained using the individual optimization as follows:

For the minimum values:

$$Min\ Z_1 = \sum_{i \in I} C_i^p q_i + \sum_{i \in I} C_i^a u_i + \sum_{i \in I} C_i^t \left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{32}$$

$$Min\ Z_2 = \sum_{i \in I} CO_{2i} \left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{33}$$

$$Min\ Z_3 = \sum_{i \in I} w_i^s q_i \tag{34}$$

$$Min\ Z_4 = CW \left(\sum_{i \in I} w_i^c q_i \right) + GW \left(\sum_{i \in I} w_i^g q_i \right) + \text{S}W \left(\sum_{i \in I} w_i^s q_i \right) \tag{35}$$

For the maximum values:

$$Max\ Z_1 = \sum_{i \in I} C_i^p q_i + \sum_{i \in I} C_i^a u_i + \sum_{i \in I} C_i^t \left\lceil \frac{q_i}{TC} \right\rceil d_i \tag{36}$$

$$Max\ Z_2 = \sum_{i \in I} CO_{2i} \left\lceil \frac{q_i}{TC} \right\rceil d_i \quad (37)$$

$$Max\ Z_3 = \sum_{i \in I} w_i^s q_i \quad (38)$$

$$Max\ Z_4 = CW \left(\sum_{i \in I} w_i^c q_i \right) + GW \left(\sum_{i \in I} w_i^g q_i \right) + \mathrm{S}W \left(\sum_{i \in I} w_i^s q_i \right) \quad (39)$$

3.4.1.1 Solving the optimization problem using ε -constraint

Based on this method, the FMOO model is transformed into a mono-objective model by considering one of the objectives as an objective function, and shifting other objective functions to constraint subject to ε-value (Ehrgott, 2005). The equivalent solution formula (Z) can be expressed as follows:

$$Min\ Z\ = Min\ \mathrm{Z}_1 \quad (40)$$

Subject to:

$$Min\ Z_2 \le \varepsilon_1 \quad (41)$$

$$[Z_2]^{\min} \le \varepsilon_1 \le\ [Z_2]^{\max} \quad (42)$$

$$Max\ Z_3 \ge \varepsilon_2 \quad (43)$$

$$[Z_3]^{\min} \le \varepsilon_2 \le\ [Z_3]^{\max} \quad (44)$$

$$Max\ Z_4 \ge \varepsilon_3 \quad (45)$$

$$[Z_4]^{\min} \le \varepsilon_3 \le\ [Z_4]^{\max} \quad (46)$$

And equations 27-30.

In this study, minimization of Z_1 is kept as an objective function as Eq. 40 and minimization of Z_2 and maximization of Z_3 and Z_4 are considered as constraints (Eq. 41, 43 and 45 respectively).

3.4.1.1 Solving the optimization problem using LP-metrics

Based on this method, the individual optimization for the five objective functions is applied for revealing the ideal objective values ($Z_1^*, Z_2^*, Z_3^* \text{and } \mathrm{Z}_4^*$). The FMOO model was transformed into a mono-objective model using the following formula (Al-e-hashem et al., 2011):

$$Min\ Z = \left[w_1 \frac{Z_1 - Z_1^*}{Z_1^*} + w_2 \frac{Z_2 - Z_2^*}{Z_2^*} + w_3 \frac{Z_3 - Z_3^*}{Z_3^*} + w_4 \frac{Z_4 - Z_4^*}{Z_4^*} \right] \tag{47}$$

where w_1, w_2, w_3 and w_4 are the weights of objective functions to be assigned by decision makers, subject to equations 27-30.

3.4.2 Selecting the final solution using TOPSIS

After obtaining a set of Pareto solution, decision makers should select one solution to allocate the optimal order of products to be purchased from each supplier. This selection can be accomplished according to decision makers' preferences or via a decision-making algorithm. In this work, TOPSIS is used for determining the final solution which is the closest to the ideal solution. The application steps followed in Ramesh et al. (2012) were followed.

Assume $\mathrm{PR} = \left\{ \mathrm{PR}_{\mathrm{op}} \middle| \mathrm{o = 1, 2, ..., x\ (number\ of\ pareto\ solutions);\ p = 1, 2, ..., y\ (number\ of\ criteria)} \right\}$ refers the $x*y$ decision matrix, where PR is the performance rating of alternative Pareto solutions with respect to criterion function values. Thus, the normalized selection formula is presented as follows:

$$N_{op} = \frac{PR_{op}}{\sum_{a=1}^{x} PR_{ap}} \tag{48}$$

The amount of decision information can be measured by the entropy value as:

$$E_p = \frac{-1}{\ln\ x} \sum_{o=1}^{x} N_{op} \ln(N_{op}) \tag{49}$$

The degree of divergence D_p of the average intrinsic information under p = 1, 2, 3, 4 can be calculated as follows:

$$D_p = 1 - E_p \tag{50}$$

The weight for each criterion function value is given by:

$$w_p = \frac{D_p}{\sum_{k=1}^{y} D_k} \tag{51}$$

Thus, the criterion weighted normalized value is given by:

$$v_{op} = w_o N_{op} \tag{52}$$

Where, w_o refers to a weight in alternatives which are normally assigned by the decision makers.

The positive ideal solution (AT+) and the negative ideal solution (AT^-) are taken to generate an overall performance matrix for each Pareto solution. These values can be expressed as below:

$$\begin{aligned} AT^+ &= (\max(v_{o1}) \quad \max(v_{o2}) \quad .... \quad \max(v_{oy})) = (v_1^+, v_2^+, ..., v_y^+) \\ AT^- &= (\min(v_{o1}) \quad \min(v_{o2}) \quad ... \quad \min(v_{oy})) = (v_1^-, v_2^-, ..., v_y^-) \end{aligned} \tag{53}$$

A distance between alternative solutions can be measured by the n-dimensional Euclidean distance. Thus, the distance of each alternative from the positive and negative ideal solutions is given as:

$$D_p^+ = \sqrt{\left\{\sum_{o=1}^{y} (v_{op} - v_o^+)^2\right\}} \quad , \quad p = 1, 2, ..., x \tag{54}$$

$$D_p^- = \sqrt{\left\{\sum_{o=1}^{y} (v_{op} - v_o^-)^2\right\}} \quad , \quad p = 1, 2, ..., x \tag{55}$$

The relative closeness to each of values of solutions to the value of the ideal solution is expressed as follows:

$$rc_p = \frac{D_p^-}{D_p^+ + D_p^-}, \quad p = 1, 2, ..., x \tag{56}$$

Where $D_p^- \geq 0$ and $D_p^+ \geq 0$, then, clearly, $rc_p \in [1, 0]$

The Pareto solution with the highest rc_p is selected as the final solution.

4. Application

In this section, a real case study is used for validating the applicability of the developed hybrid MCDM-FMOO approach in solving a SSS/OA problem in selecting the best sustainable suppliers of raw materials for a metal factory. Table 3 shows the used data which are collected from a factory in Saudi Arabia. Transportation distances among farms, abattoirs and retailers are estimated using Google Map. The FMOO is solved via LINGO[11] software running on a personal laptop Corei5 2.5gigahertz with 4gigbytes RAM.

The authors of the paper are engaged with real-world issues where the concept of the sustainable factory in semi-developed and developing countries such as Saudi Arabia is extremely important. It serves as a potential to preservation of the natural environment and improving the standards of living through environmental and social aspects presented in the paper, e.g. waste management, pollution reduction and staff development. The researchers spent time and patience to understand what is happening in the manufacturing facility. In addition, the methodology includes active engagement with the decision makers where they were asked to rank potential suppliers. Therefore, authors strongly believe that the paper shows the impact and relevance for a real- world issue and the Section 5 presents a discussion related to the managerial and practical implications of the research.

Table 3. Data used for applying the case study

$I = 3$	$CO_{2i} = 271, 294$
$C_i^p = 2\text{-}3$	$S_i = 500{,}000\text{-}700{,}000$
$C_i^t = 1\text{-}1.5$	$D_j = 350{,}000\text{-}500{,}000$
$C_i^a = 3\text{-}4.5$	$d_i = 120, 409$
$TC = 20{,}000$	

Table 4 illustrates the related sub-criteria for each set used for evaluating and ranking the suppliers. As shown in Table 4 there are 4 conventional criteria, 3 green criteria and 3 social criteria. Tables 5 illustrates the inputs used for evaluating and ranking three raw material suppliers (S1, S2 and S3) with respect to the three sets of criteria. Three decision makers (DM_1, DM_2, and DM_3) are asked to rank the potential suppliers. The experimental experiences of these decision makers are used to assign the importance of three sets of criteria of SSS/OA. Averagely, the decision makers had 8 years of experience in this field of supplier selection. The rating is based on the conventional criteria (C), green criteria (G) and social criteria (S).

Table 4. Criteria and sub-criteria used for ranking suppliers

Criteria	Sub-criteria
Conventional	Costs (C1) Product quality (C2) Technology capability (C3) Delivery reliability (C4)
Green	Environment Management Systems (G1) Waste Management (G2) Pollution production (G3)
Social	Safety, rights and health of employees (S1) Staff development (S2) Information disclosure (S3)

Table 5. Inputs for evaluating and ranking the suppliers

		Conventional criteria				Green criteria			Social criteria		
Criterion		C1	C2	C3	C4	G1	G2	G3	S1	S2	S3
	DM1	**VH**	**VH**	**VH**	**H**	**VH**	**VH**	**M**	**H**	**H**	**VH**
	S_1	VH	H	H	H	M	VH	H	VH	H	H
	S_2	H	M	L	H	M	M	L	H	H	H
	S_3	VH	H	VH	VM	M	VH	VH	M	L	H
	DM2	**H**	**VH**	**H**	**VH**	**H**	**H**	**M**	**M**	**M**	**VH**
	S_1	H	VH	M	H	VH	H	H	H	M	H
	S_2	H	H	L	VH	H	M	M	VH	M	M
	S_3	VH	H	VH	H	H	H	VH	L	H	M
	DM3	**VH**	**H**	**VH**	**VH**	**H**	**VH**	**VH**	**H**	**H**	**VH**
	S_1	VH	VH	M	H	M	VH	H	H	H	VH
	S_2	VH	M	H	H	M	L	M	M	M	H
	S_3	H	H	VH	VH	VH	H	VH	M	L	M

4.1 Results and discussions

The steps for solving the SSS/OA problem using the developed hybrid MCDM-FMOO approach are as follows.

Step 1: Fuzzy AHP is applied following the steps as illustrated in section 3.2 for determining the importance weight (IW) for the three sets of criteria including conventional (C), green (G) and social (S). The same algorithm is then reapplied for all sub-criteria. Table 6 shows the determined importance weights for the main and sub criteria. Consequently, the most significant sub-criteria are ordered as cost/product quality/environment management systems and waste management/information disclosure/safety, rights and health of employees. Besides, as shown in Table 6, the ranking order of the three pillars of sustainability is presented as economic/green/social.

Step 2: After determining the importance weights of all the criteria and sub-criteria for sustainable supplier selection in Step 1, potential suppliers are ranked with respect to the aforementioned criteria. Therefore, Fuzzy TOPSIS is used as illustrated in section 3.3 previously. This yields in determining an importance weight for each supplier. Table 7 shows the ranking of the three suppliers corresponding to the relevant criteria; Fig. 4 shows further comparison among the three suppliers in the obtained weights. As shown in Table 7 and Fig. 4, the ranking order based on the sustainability performance of three suppliers is given as S3/S1/S2. This indicates that supplier 3 is the best sustainable supplier and supplier 2 is the worst sustainable supplier.

Table 6. The relative importance weights of criteria and sub-criteria determined via Fuzzy AHP

Criteria	IW	Sub-criteria	IW	
Conventional	0.435 (*CW*)	C1	0.133	1
		C2	0.117	2
		C3	0.072	4
		C4	0.113	3
Green	0.291 (*GW*)	G1	0.110	1
		G2	0.091	2
		G3	0.090	3
Social	0.274 (*SW*)	S1	0.0755	2
		S2	0.0755	2
		S3	0.1230	1

Table 7. Ranking of the three suppliers using Fuzzy TOPSIS

Supplier	w_i^c	w_i^g	w_i^s	Average CC	Average Rating
S_1	0.660	0.676	0.502	0.612	2
S_2	0.544	0.555	0.532	0.543	3
S_3	0.719	0.693	0.788	0.733	1

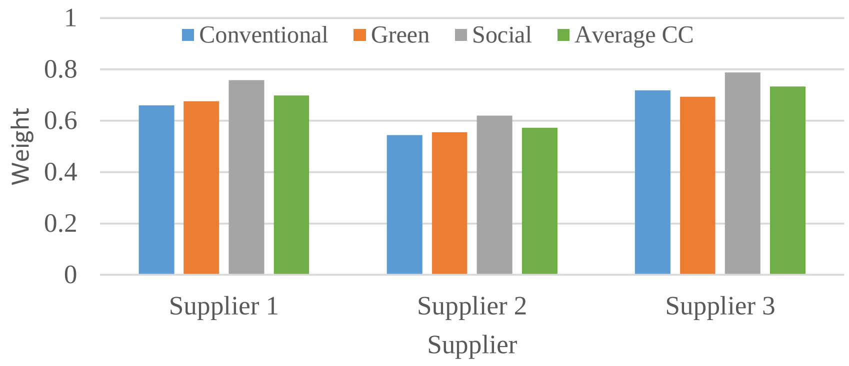


Fig. 4. Comparative of suppliers in importance weights with respect to three criteria.

Step 3: The Min and Max values for the four objectives are determined using Eq. (32-39). The values are ({Min, Max}) = ({780,220, 1,536,994}, {618,579.83, 987,664.08}, {259,200, 375,661}, {350,000, 499,842.5}). Accordingly, the ideal solutions (Z_1^*, Z_2^*, Z_3^* and Z_4^*) are: Z_1^* = 780,220, Z_2^* = 618,579.83, Z_3^* =375,661 and Z_4^* = 499,842.5).

Step 4: this step is used for obtaining the optimal order allocation using the developed FMOO model as illustrated in the following sub-step.

Step 4.1: Each objective function is optimized independently under the predefined constraints.

Step 4.2: To solve the optimization problem of the developed FMOO model formulated in section 3.2.1, the ε-constraint method and the LP-metrics method are employed for optimising the four objectives simultaneously in term of obtaining Pareto solution.

Step 4.3: for the ε-constraint: the range between the two values for Z_1, Z_2, Z_3 and Z_4 obtained in Step 3 is segmented into ten points, the points (ε-points) in between are allocated as ε values (See Table 8) in Eq. (41, 43 and 45). Subsequently, Eq. (40) is applied to reveal Pareto solutions since the objective functions minimization of Z_2 and maximization of Z_3 and Z_4 are shifted to the constraints.

Step 4.4: for the LP-metrics, Pareto solutions based on the FMOO model are obtained by applying Eq. 47 through an assignment of different combinations of weights (See Table 9) in addition to the usage of the ideal solutions (Z_1^*, Z_2^*, Z_3^* and Z_4^*) obtained in Step 3.

Step 4.5: TOPSIS is applied for ranking the obtained Pareto solutions obtained using the ε-constraint approach and the LP-metrics approach.

Table 8. ε–value assigned to Z_2, Z_3 and Z_4 to apply the ε-constraint approach

	ε –value		
#	ε_1	ε_2	ε_3
1	618579	259200	350,000
2	654579	273757	368120
3	709039	287700	386570
4	735039	302210	405178
5	770039	312722	422738
6	799039	326678	441238
7	839000	340478	458161
8	889640	354978	476170
9	947719	349006	490000
10	987664	375661	499842

Table 9. Weights assigned to Z_1, Z_2, Z_3 and Z_4 to apply the LP-metrics approach

	Assigned Weights
#	W_1, W_2, W_3, W_4
1	0.9,0.025,0.025,0.05
2	0.8,0.1,0.05,0.05
3	0.7,0.1,0.1,0.1
4	0.64,0.12,0.12,0.12
5	0.6,0.13,0.13,0.14
6	0.5,0.25,0.125,0.125
7	0.4,0.2,0.2,0.2
8	0.34,0.22,0.22,0.22
9	0.3,0.23,0.23,0.24
10	0.22,0.26,0.26,0.26

As mentioned previously, in Step 4.1, each objective function was optimized independently under the predefined constraints. Table 10 shows the obtained objectives values and the corresponding order allocation for the three suppliers. It is noteworthy that through optimizing the first objective function Z_1 individually, value of the expected cost is the lowest but this results in the lowest undesired values of social impact and total purchasing values. Optimizing the second objective function Z_2 individually, results in similar values nearly but the value of Z_2 in the lowest value. In the previous two solutions, the rank of sustainable suppliers is given as S3/S1/S2. On the contrast, optimizing the third objective function Z_3 individually leads to the highest social impact but with the highest undesired values of the expect cost and environmental impact. Optimizing the fourth objective function Z_4 individually, results in similar values nearly but the value of Z_4 is the highest value. In the previous two solutions, the rank of sustainable suppliers is given as S3/S2/S1. As shown in this solution, the order allocated to S2 become more than the order allocated to S1. This means that supplier 2 become the second best sustainable supplier with respect to the social criteria compared to the overall ranking which is S3/S1/S2.

Table 10. Objective values and corresponding order allocation obtained by optimizing the objective functions individually

Objective functions	Min Z_1	Min Z_2	Max Z_3	Min Z_4
Z_1	**780220**	643881	260008	350776
	S1	S2	S3	
	125080	104997	134886	
Z_2	800412	**618579.83**	264881	352000
	S1	S2	S3	
	127780	110556	137612	
Z_3	1495181	977881	**375661**	481701
	S1	S2	S3	
	139954	151669	183770	
Z_4	1493350	975009	359667	**499842.5**
	S1	S2	S3	
	138006	105890	180885	

To optimize the four objectives simultaneously, the ε-constraint approach and the LP-metrics approach are applied as illustrated in Steps 4.3 and 4.4, respectively. Tables 11 and 12 show the values for the four objectives based on ten ε-iteration and ten weight combinations, respectively. For instance, solution 6 in Table 11 yields an expect costs of 1,152,504, an environmental impact of 798,669, a social impact of 326,999 and a total purchasing value of 441,238. This solution is determined through an assignment of ε_1 = 799,039, ε_2 = 326,678 and ε_3 = 441,238. Fig. 5 illustrates the Pareto frontier for the obtained solution using the two methods. It is worth mentioning that ten α-level (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and1) with an incremental step 0.1 was assigned for each solution. Afterward, Eq. 31 is employed to determine the respective membership degree (μ_b) based on objective values obtained by ε-constraint approach and LP-metrics approach as shown in Tables 13. Fig. 6 depicts the corresponding figures of the membership functions with respect to the objectives values (obtained using the ε-constraint approach) for the case study.

Table 11. Objectives values obtained by the ε-constraint approach

#	α-level	Min Z_1	Min Z_2	Max Z_3	Max Z_4
1	0.1	802445	618579	259200	350,000
2	0.2	888736	652887	275547	371000
3	0.3	917699	704221	287700	387234
4	0.4	987005	731000	302210	405180
5	0.5	1067241	765773	313555	422738
6	0.6	1152504	798669	326999	441238
7	0.7	1238504	839000	343676	462008
8	0.8	1319767	889117	357000	476888
9	0.9	1389959	946340	363710	490122
10	1	1492772	976881	375661	499842

Table 12. Objectives values obtained by the LP-metrics approach

#	α-level	Min Z_1	Min Z_2	Max Z_3	Max Z_4
1	0.1	802500	620001	259312	350,000
2	0.2	889200	651990	273778	371000
3	0.3	927895	7046891	287340	387234
4	0.4	993444	733412	303209	405788
5	0.5	1100291	768345	314301	423290
6	0.6	1179999	809158	327881	442100
7	0.7	1252700	838491	341999	461711
8	0.8	1331230	910023	357120	477009
9	0.9	1387990	946801	369833	488343
10	1	1519350	979006	373338	496137

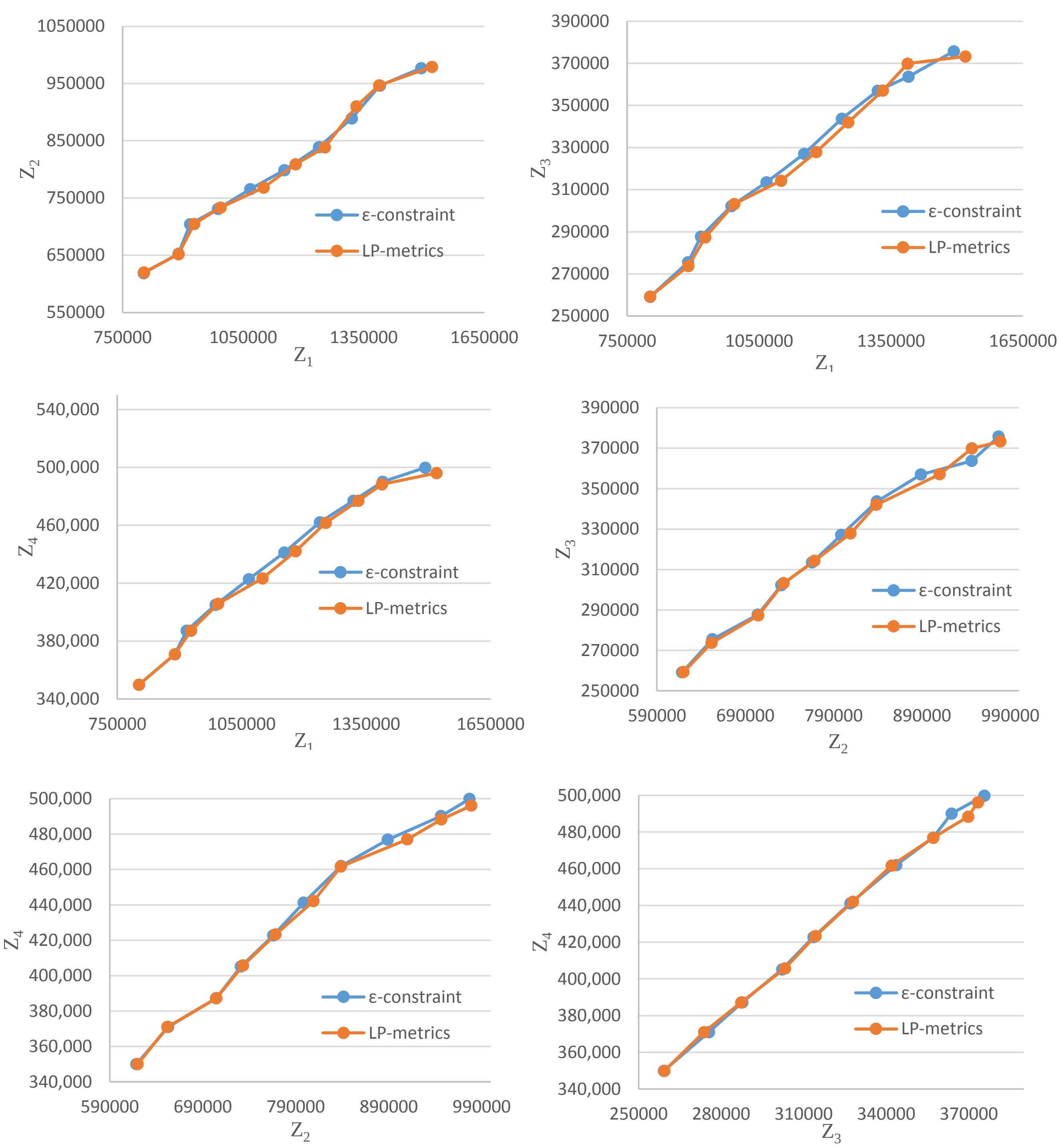


Fig. 5. Pareto frontier obtained by the two approaches.

Table 13. Values of membership degree related to Z_1, Z_2, Z_3 and Z_4 obtained by ε-constraint and LP-metrics approaches

	ε-constraint									
$\mu(Z_1)$	0.97	0.84	0.77	0.65	0.56	0.49	0.41	0.34	0.17	0.088
$\mu(Z_2)$	0.96	0.87	0.75	0.69	0.54	0.46	0.35	0.28	0.15	0.089
$\mu(Z_3)$	0.09	0.21	0.3	0.38	0.48	0.59	0.72	0.8	0.9	0.99
$\mu(Z_4)$	0.12	0.21	0.3	0.38	0.45	0.57	0.71	0.77	0.82	0.95
	LP-metrics									
$\mu(Z_1)$	0.98	0.85	0.77	0.65	0.54	0.48	0.38	0.29	0.15	0.065
$\mu(Z_2)$	0.93	0.87	0.7	0.65	0.47	0.39	0.3	0.25	0.15	0.069
$\mu(Z_3)$	0.06	0.15	0.26	0.33	0.44	0.56	0.67	0.77	0.91	0.96
$\mu(Z_4)$	0.1	0.19	0.28	0.36	0.43	0.55	0.7	0.79	0.81	0.92

The optimisation results demonstrate that considering sustainability aspects into the supplier selection and order allocation problem can yield a higher cost to the enterprise. On the contrary, this helps in improving the value of sustainable purchasing. It is noteworthy that none of the two solution methods (e.g. ε-constraint approach and LP-metrics approach) could reveal an ideal solution considering the four objectives simultaneously. Arguably, the two methods showed a reasonable performance in revealing Pareto solutions that are close enough to the ideal solutions ($Z_1^*, Z_2^*, Z_3^*$and Z_4^*). However, one solution should be selected to determine the optimal order allocation as illustrated in the next section.

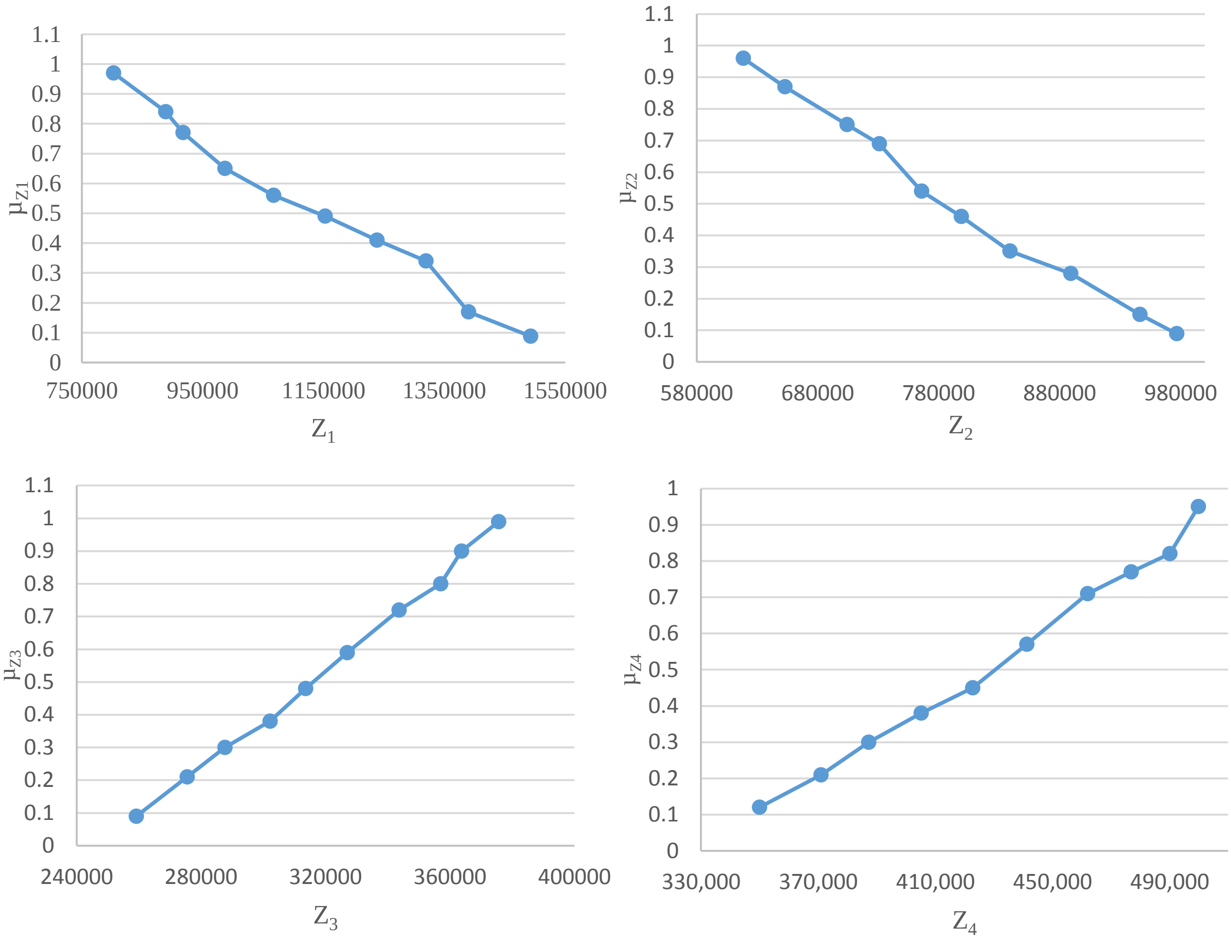


Fig. 6. Membership functions related to the four objectives Z_1, Z_2, Z_3 and Z_4 according to the ε-constraint approach.

Since a set of Pareto solutions of SSS/OA are revealed based on the developed hybrid MCDM-FMOO approach, the final Pareto solution can be selected using one of the following two scenarios:

1. Enterprises could depend on the experts of their decision makers to present some guidelines to select the final Pareto solution.
2. Some decision-making algorithms can be used to select the final Pareto solution.

However, in most fuzzy multi-objective optimization problems, the selection of the final solution can be a challenge in terms of distinguishing the final possible course of action. Therefore, as mentioned previously, TOPSIS procedures illustrated in section 3.4.2 is proposed to be applied to help decision makers in comparing the performance of the obtained Pareto solution in terms of solution quality. Fig. 7 shows a comparison in the determined rc_p for all

Pareto solutions. Averagely, the solutions obtained by the ε-constraint approach are the closest to the ideal solutions and the furthest from the nadir solutions compared to solutions obtained by the LP-metrics approach. Subsequently, solution 4 is selected as the final solution since it obtained the highest rc_p (0.699). Based on this solution the order allocation is as follows:

1. 183,335Kg to be ordered from supplier 3.
2. 145,988Kg to ordered from supplier 1.
3. 136,008Kg to be ordered from supplier 2.

As shown, supplier 3 dominates 39.39% of all the ordered raw material since it leads to the best sustainable performance compared to suppliers 1 and 2 which dominate 31.37% and 29.22%, respectively.

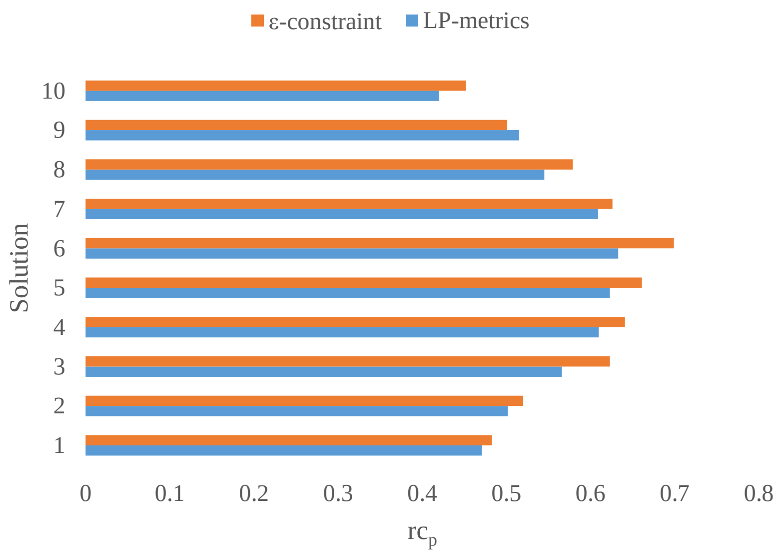


Fig. 7. A graphical comparison in rc_p between the two approaches obtained using TOPSIS.

5. Managerial and practical implications of the research

This research has determined different criteria for sustainable supplier selection on the basis of sustainability. The results demonstrated significant managerial and practical implications of the developed hybrid MCDM-FMOO approach which can be concluded as follows:

- The developed methodology for solving the sustainable supplier selection and order allocation problem can be used as an aid for enterprises in implementing an integrated framework to select the best sustainable suppliers.

- The developed approach can effectively support decision makers to order the appropriate quantity of product from each supplier.
- The considered three sets of criteria and sub-criteria related to economic, environmental and social aspects can be implemented in other applications examining a sustainable supplier selection and order allocation problem.
- The developed approach can be employed for solving another case studies in solving sustainable supplier and order allocation problem in conjunction with the optimization of several conflicting objectives.
- In industry, decision makers typically deal with a conflicting uncertain multi-objective problem required to be solved simultaneously by them in a comprised level. Therefore, using the fuzzy set theory for SSS/OA leads to more effectiveness and flexibility for the developed hybrid approach. Subsequently, the developed hybrid MCDM-FMOO approach complies with the practical application necessities for handling a real SSS/OA problem through the simultaneous minimization of expected cost and environmental impact and maximization of social impact and purchasing value.
- This approach can successfully cope with the vagueness and imprecision of input parameters and the changing importance weight of criteria in a SSS/OA problem.
- The developed approach offers a flexibility to purchasing manager(s) to perform a robust sustainable supply chain management on cost, product quality, on time delivery, environmental and social aspects, etc.

6. Conclusions and future works

Recently, sustainable supply chain management is gaining an increasing consideration among enterprises all over the world and managers are under pressure to consider sustainable practices in their supply chain activities. An effective Sustainable Supplier Selection and Order Allocation (SSS/OA) methodology can lead to an increase competitiveness for an enterprise. The literature review shows that the SSS/OA methodologies requires a substantial improvement in counting social performance into consideration rather focusing on economic-environmental aspects. This papers presents a development of a hybrid Multi-Criteria Decision Making (MCDM)-Fuzzy Multi-Objective Optimization (FMOO) approach for SSS/OA problem by considering economic, environmental and social criteria. First, the criteria and sub-criteria for evaluating sustainable performance are highlighted. Second, the decision makers give linguistic ranking to the criteria and suppliers. Fuzzy AHP is used for determining the importance weights of criteria; Fuzzy TOPSIS is used for generating the overall rank of suppliers. Third, a fuzzy multi-objective model is developed to determine the optimal order allocation in minimizing the expected cost and environmental impact and maximizing the social impact and total purchasing value. Fourth, to obtain Pareto solution derived from the developed fuzzy multi-objective model, two solution approaches are employed including the ε-constraint approach and the LP-metrics approach. Finally, TOPSIS is used as an aid to decision makers is selecting the final Pareto solution. A real case study is used to show the applicability and effectiveness of using the developed MCDM-FMOO approach to the SSS/OA problem under multiple uncertainties. Managerial and practical implications of the research are presented based on the obtained results. The ongoing research work is to apply the developed approach in solving SSS/OA problems for two SMEs in Cardiff city/UK.

Since the number of potential suppliers are limited to three in this research, the advantage of the developed approach will be seen much clearer with the number of suppliers grows. Compare the performance of the Fuzzy AHP-Fuzzy TOPSIS with other MCDM approaches such as ELECTRE and VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje) can be a future research avenue. Also, sensitivity analysis can be performed to investigate the robustness of the proposed approach.

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