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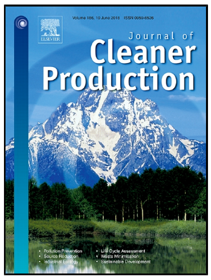

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An integrated model for solving problems in green supplier selection and order allocation

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Abstract

Green purchasing is a critical factor in sustainable enterprise development, and it often affects a company's business performance and environmental protection practices. An enterprise must have an appropriate assessment model to address the complexities of green purchasing. Most green purchasing studies have focused on the use of green criteria in the selection of suppliers to develop sustainable operations. By contrast, there have been few articles on green supply chain management discussing both green supplier evaluation and order allocation. This study proposes a novel model that integrates the best–worst method, modified fuzzy technique for order preference by similarity to ideal solution (TOPSIS), and fuzzy multi-objective linear programming to solve problems in green supplier selection and order allocation. We demonstrated the proposed method using actual data provided by an electronics company. The results indicate that this model can effectively evaluate the performance of green suppliers and can also optimize order allocation for qualified suppliers.

Keywords: green supplier selection, BWM, modified fuzzy TOPSIS, FMOLP, order

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allocation, procurement strategy.

1. Introduction

The goal of green supply chain management (GSCM) is a thorough integration of logistical and financial information to increase the competitiveness of supply chain units' products or services, resulting in sustainable enterprise development and improved environmental protection (Wan et al., 2017; Sarkar et al., 2017). The leading global enterprises have recognized the urgency of the need to take measures for environmental protection and have begun to change their own policies and practices to conform to these goals. Thus, the procurement of raw materials in compliance with environmental regulations has already become a basis for the evaluation of green partners (Lu et al., 2007). Many in the manufacturing industry have adjusted their production concepts and fostered the introduction of environmental awareness into their organizations. Some have also, established environmental standards for the management of scrap products and take into consideration the recyclability of the raw materials obtained from their suppliers (Chen et al., 2012). Manufacturing firms typically spend approximately 60% of their total income on purchasing raw materials and components. For high-tech manufacturers, this amount can be as high as 80% (Kokangul and Susuz, 2009; Lee and Drake, 2010) meaning that purchasing strategies are very critical in GSCM. Selecting suitable firms as suppliers of products or services requires the consideration of numerous complex factors and thus qualifies as a multi-criteria decision-making (MCDM) problem (Kumar et al., 2017).

Given the current background of rising environmental protection consciousness, enterprises must pay attention to saving energy, waste elimination, parts interchangeability, ease of disassembly, and recyclability. Thus, green supplier management and purchasing are becoming increasingly critical (Lin et al., 2011). Manufacturers typically purchase the same raw materials or components from several suppliers, especially when a single supplier is unable to satisfy the demand due to capacity and risk-sharing limitations. This requires a compromise solution based on the manufacturer's enterprise sustainability policy and environmental purchasing objectives (Govindan and Sivakumar, 2016). A few studies have discussed the integration of green supplier selection and order allocation. Most of these studies have applied MCDM models. In general, the MCDM process is categorized as multiple attribute decision-making (MADM) or multiple objective decision-making (MODM) on the basis of the problem's solution space (i.e., whether the solution space is continuous or discrete) (Liou and Tzeng, 2012). MADM is a qualitative approach that utilizes several criteria and a small sample of expert questionnaires to establish a supplier evaluation model that can integrate the comprehensive performance of each supplier, identify qualified partners, and assist suppliers to develop strategies for improvement (Karsak and Dursun, 2016). The MADM approach of supplier evaluation can be explored using several methods, including the analytic hierarchy process (AHP) (Kumar et al., 2017), the analytic network process (ANP) (Wan et al., 2017), the best–worst method (BWM) (Rezaei et al., 2015), the decision-making trial and evaluation laboratory (DEMATEL) (Govindan et al., 2015), the technique for order preference by similarity to ideal solution (TOPSIS) (Chen, 2016), *visekriterijumska optimizacija i kompromisno resenje* (VIKOR) (Luthra et al., 2017; Sarkar et al., 2017), preference ranking organization method for enrichment evaluation (PROMETHEE) (Behzadian et al., 2010; Govindan et al., 2017; Marttunen et al., 2017) and elimination and choice translating reality (ELECTRE) (Govindan and Jepsen, 2016; Marttunen et al., 2017; Wan et al., 2017). At present, several MADM models are widely used in various industries for supplier performance management (Rajesh and Ravi, 2015; Gupta and Barua, 2017). By contrast, MODM considers several objectives and restrictions to establish a purchasing order allocation model (Osiro et al., 2014). Common MODM methods include linear programming (LP) (Soto et al., 2017), integer linear programming (Kaur et al., 2016), mixed integer linear programming (Ghaniabadi and Mazinani, 2017), goal programming (Hu and Vincent, 2016), fuzzy goal programming (Tsai and Hung, 2009), and fuzzy multi-objective linear programming (FMOLP) (Su and Lin, 2015; Zhou et al., 2016). In recent years, several studies have applied artificial intelligence methods to execute this analysis, for example, the neural network method (Özkan and İnal, 2014), case-based reasoning (Sarkar and Mohapatra, 2006), and heuristic algorithms (Wu et al., 2017). These methods have been employed specifically for analyzing green supplier selection and procurement strategy issues and have established an excellent basis for further research.

A review of the literature review shows that many MCDM methods have been applied to the problems of supplier evaluation or order allocation. However, there have been only a few green purchasing studies that have applied integrated MADM and MODM models to discuss GSCM problems. Integrating the experience and expertise of researchers to establish a performance evaluation model and using this assessment method to develop supplier purchase strategies can increase the reliability of supplier order allocation. Therefore, this study proposes a novel integrated model to study the selection of green suppliers and order allocation. First, according to a review of the relevant literature and the requirements of the subject firm, we construct a green evaluation system and derive criteria weights using the BWM. The BWM is used in this model because it is a useful way to determine the weights of the criteria. The BWM questionnaires are not only easy to answer but also have a higher degree of consistency than the popular AHP method. Second, a modified fuzzy TOPSIS is applied to select and rank the green suppliers. In addition, combining the weights obtained from the BWM and modified fuzzy TOPSIS method, as in done in this study, allows us to integrate supplier performance into a ranking index, which is a more reliable strategy, with consideration of information uncertainty. Finally, based on the supplier ranking index from the modified fuzzy TOPSIS and the goals of the company policy, we use FMOLP to establish an order allocation model. FMOLP makes it easy to obtain a compromise solution while considering several different goals. The obtained order allocation results take into consideration supplier performance and several goals, for the provision of an optimal purchasing strategy.

This study establishes a novel hybrid model that is suitable for use in an environment of dynamic cooperation, as well as a purchasing strategy that can be adjusted to account for internal and external changes. The results of each stage of the analysis can be included in a firm's internal knowledge management system for improved GSCM. In summary, the proposed model has four key features: (i) the model obtains green criteria weights using BWM, which requires relatively fewer pairwise comparisons and can achieve consistent results more easily than AHP; (ii) the model employs modified fuzzy TOPSIS and FMOLP assessments to address information uncertainty; (iii) the model uses an augmented max–min model, which more effectively determines total utility values than the traditional max–min model in FMOLP; (iv) the augmented max–min model can obtain a compromise solution without complex coding to generate a set of Pareto solutions.

The remainder of this paper is organized as follows. Section 2 introduces a review of the literature on GSCM, green supplier selection, and order allocation planning. Section 3 describes the methodology of the proposed hybrid model. Section 4 presents a real-world application to demonstrate the feasibility and usefulness of the proposed model. Section 5 summarizes the discussion and provides a conclusion.

2. Review of relevant literature

Because of increased environmental regulation and environmental consciousness, GSCM has received considerable attention in academic and business circles. Companies must apply GSCM strategies to react to market pressures and exhibit responsiveness to social responsibility. Green supplier selection is critical in GSCM, which includes numerous qualitative and quantitative factors and is thus a MCDM problem. Green supplier selection has been discussed by several researchers (Zouggari and Benyoucef, 2012; Govindan et al., 2015; Parkouhi and Ghadikolaei, 2017). In addition to supplier selection, order allocation is also a critical decision-making process in GSCM (Hamdan and Jarndal, 2017).

Whereas most prior studies have addressed supplier selection or order allocation problems individually, we identify some relevant studies that directly or indirectly discuss both green supplier selection and order allocation problems. Lin et al. (2011) integrated the ANP and LP methods to address green purchasing plans in the electronics industry. Their model has been used by printed circuit board firms as a green supplier selection and purchasing plan tool to support their purchasing departments' efforts to determine order quantity rapidly and to allocate orders more effectively. Yeh and Chuang (2011) developed a model with four objectives (minimum cost and total time; maximum product quality and green appraisal scores) and nine constraints. They applied a multi-objective genetic algorithm to seek near-optimum solutions for green supplier selection and product volume transportation problems. Mafakheri et al. (2011) developed a two-stage evaluation model for order allocation decision-making that considers the independence of green supplier criteria. Their model's 21 selected criteria were derived from the literature (Humphreys et al., 2003; Kokangul and Susuz, 2009). Their model applies AHP to determine criteria weights and dynamic programming to solve the allocation problem. Shaw et al. (2012) employed fuzzy AHP to determine green criteria weights and used MOLP to formulate supplier purchasing plans for garment manufacturing companies. The objective function and constraint formula used in this study considered carbon emissions. Zouggari and Benyoucef (2012) further developed this green supplier evaluation and order allocation model by applying a four-stage knowledge simulation approach. Their approach integrates supplier selection with order allocation and efficiently uses GSCM decision-makers' expertise through a knowledge-based system for order plan enhancement in dynamic supply chains.

Recently, researchers have proposed hybrid MCDM models that can strengthen the reliability of green purchasing. For example, Govindan and Sivakumar (2016) demonstrated that a proposed order allocation model based on green supplier evaluation is more effective than conventional models. Their model applies fuzzy TOPSIS and MOLP to assign purchase orders for four paper manufacturing suppliers. They employ four objectives to minimize cost, late delivery, material rejection, and CO_2 emissions in the production process. A similar model developed by Hamdan and Cheaitou (2017a) considers all unit quantity discounts for real-world order allocation situations. Their results demonstrated that an integrated model can provide decision-makers with more practical reference information. Moreover, Hamdan and Cheaitou (2017b) developed an information ambiguity model that applies weighted comprehensive criteria and a branch-and-cut algorithm under fuzzy sets to assess the purchasing quantity of suppliers. They applied the model to the real-world case of a facilities management company to illustrate its accuracy, effectiveness, and flexibility. Kannan et al. (2013) determined five indicators for evaluating green suppliers, including cost, quality, delivery, technology capability and environmental competency. The supplier performance values were obtained by using fuzzy AHP and fuzzy TOPSIS. Govindan et al. (2013) explored sustainable supply chain initiatives and examined the issue of identifying an effective model based on the Triple Bottom Line (TBL) method for supplier selection in GSCM.

In addition, the latest research for GSCM, Gören (2018) presented a GSCM decision framework for online retailer company. The study applied DEMATEL to determine the weights of the dependent criteria, and Taguchi Loss Functions was used to calculate the performance value of each supplier. The ranking of suppliers was different from the common MCDM methods (e.g. VIKOR, TOPSIS, PROMETHEE, or ELECTRE). Park et al. (2018) used multi-attribute utility theory and multi-objective integer linear programming to discuss multiple sourcing and multiple product design problems. Their study considered total cost, carbon footprint, order defect, and delivery delay as multi-objectives to be minimized respectively. In same year, a hybrid SWOT-QFD combined bi-objective two-stage mixed possibilistic-stochastic systematic framework for solving sustainable issues was proposed by Vahidi et al. (2018). This method obtained several efficient (Pareto-optimal) solutions, which the most preferred one could be selected according to the top decision maker's preferences. The preceding studies have demonstrated that order allocation models that are based on green supplier evaluation and consider the relative weights of green criteria, information uncertainty, and the aggregating mode are effective in determining purchasing plans.

We summarize the GSCM models that have integrated green supplier evaluation and order allocation in Table 1.

/Please insert **Table 1** here/

As shown in the literature review, criteria weights have most often been calculated by AHP or ANP, both requiring time-consuming pairwise comparisons and thus it is not easy to obtain consistent results. The above shortcomings can be remedied by using BWM to calculate the criteria weights. The original TOPSIS method only considers the positive and negative ideal solutions, which might not be the most appropriate way to obtain rankings in some situations (Opricovic and Tzeng, 2004). Our modified TOPSIS method considers all alternatives as reference points, making it more reliable than the original TOPSIS method (Kuo, 2017). The traditional MODM generates a set of Pareto solutions, but decision maker still needs to select a solution from this set of solutions. Furthermore, a complex algorithm and coding process are needed to obtain the Pareto solutions. Our augmented max–min FMOLP model can obtain a compromise solution without the need for complex coding processes (Arikan, 2013).

3. Proposed approach: a novel hybrid combining BWM, modified fuzzy TOPSIS, and FMOLP

This section introduces a novel hybrid green purchasing model that combines MADM and MODM. The model uses MADM to evaluate green supplier performance, BWM to derive criteria weights, and modified fuzzy TOPSIS to calculate supplier rankings that companies can use to select the most suitable suppliers. Next, the model applies fuzzy MODM to determine order allocations for each qualified supplier. Fig. 1 illustrates the basic concepts of BWM, modified fuzzy TOPSIS and FMOLP. Appendix A presents the details of the mathematical formulas.

/Please insert **Fig. 1** here/

4. Case illustration

In this section, we describe the application of the proposed integrated model to a real-world case to illustrate its usefulness. The subject company set up an evaluation team to provide actual supplier data and production requirements, which we used to build a novel model that combines BWM, modified fuzzy TOPSIS, and FMOLP to help the company select suppliers and determine a procurement plan.

4.1 Problem description and identification of criteria

Various MCDM methods have been developed to study green supplier evaluation and order allocation planning. However, these subjects have usually been studied separately; only a few studies have discussed them together. Thus, our study is divided into two stages: supplier selection and order allocation. If qualified suppliers can meet a company's needs though proper order allocation, the company will achieve increased profit and efficiency. The subject company is an electronics manufacturing firm in Taiwan. The company's products consist of motherboards, display cards, computer peripherals, personal computers, notebook computers, and network server products. Due to a high level of competitiveness in the global electronics industry and cost-reduction pressure from customers, the subject company outsources production of its noncore products and components. Selecting qualified suppliers and allocating orders to them are thus critical challenges for the company's managers and have a substantial bearing on its continued market competitiveness.

Currently, the case company is facing several problems due to market competition and regulatory requirements. First, their current supplier evaluation system does not fully take into account environmental factors and they have no systematic way to evaluate their green suppliers. Second, the weights of their evaluation criteria are determined subjectively by department managers, and different managers assign different weights for prioritizing the factors used in decision-making. Third, their purchasing plans are not based on the results of supplier evaluation. Purchasing department managers tend to allocate orders based on their own subjective experience. Although the case company does have a supply chain management system, the system is neither complete nor integrated. The case company urgently needs a system for order allocation capable of integrating the results of supplier audits with consideration of uncertain managerial judgements.

The model proposed in this study is demonstrated by using it to evaluate the case firm’s outsourced computer purchasing practices. To undertake a comprehensive assessment, eight managers from the firm’s purchasing, production management, quality control, and R&D departments were invited to form a decision-making group. The duties of these eight managers entail a very high degree of connectivity with suppliers, including procurement bargaining, inspection and control of materials, changes in component designs, etc. Each of these managers has had more than 10 years of work experience at the subject company. Furthermore, although from different departments and with different job responsibilities, supplier assessments made from different perspectives, are considered equal in importance.

The criteria for green supplier selection criteria were obtained by reviewing the relevant literature (Kuo et al., 2010; Kuo and Lin, 2011; Chen et al., 2012; Govindan et al., 2015; Rajesh and Ravi, 2015; Rezaei et al., 2016; Çebi and Otay, 2016; Uygun and Dede, 2016) and engaging in a series of discussions with the subject company’s managers. In addition to the supplier evaluation criteria obtained from the literature review, the decision group considered other factors based on the case company's products, culture, background, competitive market advantage, and current strategies, to decide on the most suitable evaluation criteria. The evaluation comprised three dimensions, 10 criteria, and six potential alternative suppliers (suppliers S_1 to S_6). The three dimensions were supplier performance (D_1), environmental protection (D_2) and supplier risk (D_3); each dimension comprised three to four criteria (see Fig. 2). We then distributed BWM and performance surveys to the eight managers to make pairwise comparisons among the 10 criteria and to evaluate the performance of the six suppliers with respect to the 10 criteria. The criteria and their descriptions are listed in Table 2.

Some studies have considered cost as a performance factor at the supplier selection stage but also have used cost as an objective function at the order allocation stage. This double counting exaggerates the importance of cost. Therefore, our study did not consider cost in the supplier performance criteria, but employed a minimum cost objective function at the order allocation stage.

/Please insert **Fig. 2** here/

/Please insert **Table 2** here/

4.2 Determination of criteria weights

We applied BWM to obtain criteria weights, as outlined in Appendix A.1. The managers were asked to compare their identified best dimension with each of the other dimensions and formulate their preferences on a scale of 1-9 (the larger the number on the scale, the more important the ranking). For example, manager 1 considered D_2 to be the best dimension, twice as important as D_1. The BO vectors are presented in Table 3. Similarly, the respondents were asked to rate the other dimensions over the worst dimensions. The OW vectors are shown in Table 4. A set of weights is obtained for each manager based on BO and OW vectors. By solving Eq. (A2), we can determine the weight of each dimension. All criteria weights were derived by following the same procedures. Because each manager had a different background and level of experience, the weights calculated for the various questionnaires were not identical. We calculated the optimal weights by arithmetical means (Rezaei et al., 2016).

The consistency ratio (*CR*) is a measure of the reliability of the BWM questionnaire. Table 5 presents the average of the eight managers' results. All *CR* values are less than 0.1. The *CR* of each questionnaire was less than 0.05, and the average *CR* was 0.0295, indicating that the questionnaires were highly consistent (Rezaei, 2015). Table 6 illustrates the integrated results of the eight manager questionnaires. The top five criteria rankings were product quality (C_{11}), innovation capability (C_{22}), service flexibility (C_{13}), green manufacturing (C_{12}), and environmental performance (C_{21}). Apart from product quality, the managers deemed development capability and environmental protection to be crucial criteria due to the company's pursuit of sustainable development and innovation. Next, we applied modified fuzzy TOPSIS to consolidate the performance data and the criteria weights for supplier selection.

/Please insert **Table 3** here/
/Please insert **Table 4** here/
/Please insert **Table 5** here/
/Please insert **Table 6** here/

4.3 Supplier performance evaluation and supplier selection

The green supplier selection process is complicated and difficult. MADM is an effective solution to this problem because it simplifies the analytical process and provides results that can meet manager expectations and suggest relevant improvement strategies. This study used TOPSIS technology and fuzzy theory to strengthen the analytical model given the uncertainty of managerial opinion. The modified TOPSIS was used because it does not need a series of pairwise comparisons as other MADM models (e.g., PROMETHEE). Also, the model is more straightforward for managers evaluating the alternatives and saving the survey time.

Step 1. Integrating managers' opinions to calculate trapezoidal fuzzy numbers

Translating managers' subjective opinions into numerical values is difficult. The trapezoidal fuzzy number is a useful solution for converting qualitative terms into fuzzy numbers. Table 7 summarizes the seven classifications that we used in our questionnaires, which were very poor (VP), poor (P), medium-poor (MP), fair (F), medium-good (MG), good (G), and very good (VG). Table 8 summarizes the evaluation of the first supplier (S_1) by the eight managers. For example, the first manager expressed that the performance of S_1 based on C_{11} was G. Table 9 illustrates the integrated initial fuzzy performance matrix for the six potential suppliers.

/Please insert **Table 7** here/

Step 2. Converting initial fuzzy matrix to normalized fuzzy matrix

The ten criteria used in this study are all benefit based criteria. We converted the initial fuzzy matrix to a normalized fuzzy matrix $\tilde{R}$ by using Eq. (A5) (Table 10).

Step 3. Integrating normalized fuzzy matrix into weights

Using Eq. (A6), we calculated a weighted normalized fuzzy matrix $\tilde{V}$ (Table 11). In this step, the criteria weights are crucial as they can substantially affect the final results of the analysis.

Step 4. Calculating distance from positive ideal solution and negative ideal solution for each supplier

According Eqs. (A7) and (A8), we obtained the fuzzy positive ideal solution (FPIS) ($\tilde{A}^*$) and fuzzy negative ideal solution (FNIS) ($\tilde{A}^-$) as follows:

$$\tilde{A}^* = [0.\widetilde{294}, 0.\widetilde{109}, 0.\widetilde{121}, 0.\widetilde{084}, 0.\widetilde{161}, 0.\widetilde{073}, 0.\widetilde{01}, 0.\widetilde{073}, 0.\widetilde{036}, 0.\widetilde{039}]$$

$$\tilde{A}^- = [\tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}]$$

The separation of a supplier S_i from the FPIS (d^*) and FINS (d^-) was calculated by using Eqs. (A9) and (A10).

Step 5. Calculating RC_i and supplier priority order

The closeness coefficient (CC_i) is obtained through TOPSIS. We obtained CC_i by using Eq. (A11). To keep CC_i in a range of 0 to 1, we derived a supplier sequence evaluation index (RC_i) (Table 12) for executing subsequent FMOLP operations by using Eq. (A12).

/Please insert **Table 8** here/
/Please insert **Table 9** here/
/Please insert **Table 10** here/
/Please insert **Table 11** here/

As indicated in Table 12, the ranking of suppliers was $S_4 \succ S_1 \succ S_2 \succ S_3 \succ S_6 \succ S_5$. Excellent suppliers normally have RC_i values of greater than 0.5 as their evaluation results are much closer to the desired values. By contrast, suppliers that have RC_i values of less than 0.5 might consider developing relevant improvement strategies. The managers selected as partners the top four suppliers by rank, namely S_4, S_1, S_2, and S_3.

/Please insert **Table 12** here/

4.4 Multi-objective order allocation model

This study further investigated the optimal order allocations for the selected qualified suppliers by using a multi-objective order allocation model. The allocation model factored in a discount for each qualified supplier when procurement exceeded a certain quantity. This resulted in two price levels (j = 1, 2), under which production lead time differed. Detailed supplier information is listed in Table 13. We used total product demand and average lead time to calculate triangular fuzzy numbers. The acceptable level was 0 when total product demand was lowest (25,500 units) and highest (27,000 units); that is, total demand had to be between 25,500 and 27,000 units. Satisfaction was highest when the average production lead time was 6 days.

/Please insert **Table 13** here/

Because allocating supplier orders is a MOLP problem, this study considered various factors in the procurement process, including procurement lead time, defect rate, quantity discounts, and capacity limitations. Our proposed order allocation model was developed with reference to Arikan (2013), Çebi and Otay (2016), and Kumar et al. (2017). Instructions for building the model and its solution process are provided as follows:

Step 1. Building the order allocation model

First, we defined the parameters of the MOLP model, as illustrated in Table 14.

/Please insert **Table 14** here/

After discussions with the subject company's managers, we defined four objective functions: cost, delivery performance, product quality, and total utility. The cost objective function considered total cost in the period between sending orders and receiving finished products (Eq. (A28)). We evaluated delivery performance by using the delay ratio, which is a risk management factor (Eq. (A29)). We measured product quality by the number of defective products, which is termed the defect rate (Eq. (A30)). The utility goal is to maximize the organizational utility using the results obtained from MADM (Eq. (A31)).

$$\min\ Z_1 = \sum_{i=1}^{I}\sum_{i=1}^{J}\sum_{k=1}^{K} c_{ijk}x_{ijk} \tag{1}$$

$$\min\ Z_2 = \sum_{i=1}^{I}\sum_{i=1}^{J}\sum_{k=1}^{K} l_{ijk}x_{ijk} \tag{2}$$

$$\min\ Z_3 = \sum_{i=1}^{I}\sum_{i=1}^{J}\sum_{k=1}^{K} d_{ijk}x_{ijk} \tag{3}$$

$$\max\ Z_4 = \sum_{i=1}^{I}\sum_{i=1}^{J}\sum_{k=1}^{K} w_{ijk}x_{ijk} \tag{4}$$

The constraints are listed in Eqs. (A32)-(A39) and include average production lead time, fuzzy demand, capacity limitation, quantity discount level, nonnegativity, and 0-1 constraints. Table 13 and Table 14 list the input data and parameters.

$$\sum_{j=1}^{J}\sum_{k=1}^{K} L_k x_{ijk} \Bigg/ \sum_{j=1}^{J}\sum_{k=1}^{K} x_{ijk} = \bar{L}_i,\ i=1,\ 2,\dots,\ I \tag{5}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K} x_{ijk} \geq \tilde{D}_i,\ i=1,\ 2,\dots,\ I \tag{6}$$

$$\sum_{j=1}^{J} x_{ijk} \leq c_{ik},\ i=1,\ 2,\dots,\ I;\ k=1,\ 2,\dots,\ K \tag{7}$$

$$x_{ijk} \leq \left(V_{ijk}-1\right) y_{ijk},\ i=1,\ 2,\dots,\ I;\ j=1,\ 2,\dots,\ J;\ k=1,\ 2,\dots,\ K \tag{8}$$

$$V_{ijk} y_{ijk} \leq x_{ijk},\ i=1,\ 2,\dots,\ I;\ j=1,\ 2,\dots,\ J;\ k=1,\ 2,\dots,\ K \tag{9}$$

$$x_{ijk} \leq D_i y_{ijk},\ i=1,\ 2,\dots,\ I;\ j=1,\ 2,\dots,\ J;\ k=1,\ 2,\dots,\ K \tag{10}$$

$$\sum_{j=1}^{J} y_{ijk} \leq 1,\ i=1,\ 2,\dots,\ I;\ j=1,\ 2,\dots,\ J;\ k=1,\ 2,\dots,\ K \tag{11}$$

$$x_{ijk} \geq 0;\ y_{ijk}=0,\ 1,\ i=1,\ 2,\dots,\ I;\ j=1,\ 2,\dots,\ J;\ k=1,\ 2,\dots,\ K \tag{12}$$

Step 2. Determining optimal upper and lower bounds

We obtained optimal upper and lower bounds of the four objective functions by using Eqs. (A13)-(A14), as illustrated in Table 15.

/Please insert **Table 15** here/

Step 3. Determining membership functions

For minimization objectives (Z_1 to Z_3), membership functions were established using Eq. (A18); for the maximization objective (Z_4), Eq. (A19) was used to formulate the membership function. We applied Eq. (A20) to establish the membership functions for constraints.

Step 4. Transforming the FMOLP problem into a linear model

Based on the proposed FMOLP model (Appendix A.3) and membership functions established in Step 3, we transformed the MOLP problem into a linear programming model expressed as Eq. (13).

$$\max = \lambda + \left[\left(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_d + \lambda_l\right)/6\right]$$

s. t.

$$\lambda_1,\ \lambda_2,\ \lambda_3,\ \lambda_4,\ \lambda_d,\ \lambda_l \geq \lambda$$

$$\lambda_1 \leq \frac{766143 - z_1(x)}{677750},\quad \lambda_2 \leq \frac{815 - z_2(x)}{165.5},\quad \lambda_3 \leq \frac{613 - z_3(x)}{103.5},\quad \lambda_4 \leq \frac{z_4(x) - 12420.5}{1357}$$

$$\lambda_d \leq \left(\left(\sum_{j=1}^{2}\sum_{k=1}^{4} X_{jk} - 25500\right)/500\right),\quad \lambda_d \leq \left(\left(27000 - \sum_{j=1}^{2}\sum_{k=1}^{4} X_{jk}\right)/1000\right)$$

$$\lambda_l \leq \left(\left(\left(2x_{11} - x_{22} + 2x_{13} + x_{23} + x_{14}\right) - 5\right)/1\right),\quad \lambda_l \leq \left(\left(7 - \left(2x_{11} - x_{22} + 2x_{13} + x_{23} + x_{14}\right)\right)/1\right)$$

$$x_{11} + x_{21} \leq 8500,\ x_{12} + x_{22} \leq 9000,\ x_{13} + x_{23} \leq 9500,\ x_{14} + x_{24} \leq 10000$$

$$x_{11} \le 4999 y_{11},\ 5000 y_{21} \le x_{21},\ x_{21} \le 8500 y_{21}$$

$$x_{12} \le 5499 y_{12},\ 5500 y_{22} \le x_{22},\ x_{22} \le 9000 y_{22}$$

$$x_{13} \le 5799 y_{13},\ 5800 y_{23} \le x_{23},\ x_{23} \le 9500 y_{23}$$

$$x_{14} \le 6499 y_{14},\ 6500 y_{24} \le x_{24},\ x_{24} \le 10000 y_{24}$$

$$y_{11} + y_{21} \le 1,\ y_{12} + y_{22} \le 1,\ y_{13} + y_{23} \le 1,\ y_{14} + y_{24} \le 1$$

$$y_{jk} = 0,\ 1;\ x_{jk} \ge 0;\ j = 1,\ 2;\ k = 1,\ 2,\ 3,\ 4$$

$$\forall x_{jk} \in interger \tag{13}$$

Step 5. Obtaining order allocation results

Table 16 illustrates the results of Eq. (13) with six utility variables and 16 decision variables. Consider the first objective as an example: The minimum purchase cost utility value was 0.692, and the objective value was \$705,018. The demand utility and average lead time utility values were 1, meaning that the results achieved the company's desired values. The final order allocations and unit prices for the four suppliers were as follows: S_1 received an order for 8,500 units at a unit price of \$26.5; S_2 received an order for 5500 units at a unit price of \$27.5; S_3 received an order for 2753 units at a unit price of \$32; and S_4 received an order for 9247 units at a unit price of \$26. The quantity required to receive a discount was not reached only for supplier S_3.

/Please insert **Table 16** here/

5. Discussion and conclusions

Supplier selection and order allocation are critical problems in GSCM. Few prior studies have considered both problems simultaneously. The indicators or criteria for green supplier performance evaluation can be divided into qualitative and quantitative types. The indicator values obtained through measurement produce quantitative data, such as the defective rate, stock-out rate and price. Some indicators entail subjective assessment, for example, of environmental performance, service quality, reputation, information security, etc. Combining both types of indicators to measure supplier performance is a complex problem. In addition, the different viewpoints of the various department managers in the case company make the process of linking supplier performance with order allocation more difficult. For example, the purchasing department considers cost to be most important, while quality assurance deems quality to be the most essential factor. Therefore, this study combined MADM and MODM models to establish an integrated model to help companies select the most qualified suppliers and allocate orders to them. Our proposed model improved on the model proposed by Kannan et al. (2013) in several aspects. First, we obtained the criteria weights from BWM, which is an efficient and effective method of deriving the criteria weight vectors in the analyzed MADM problems because it requires fewer pairwise comparisons and easily obtains consistent results. Second, ranking indices in our model were calculated using modified TOPSIS, as proposed by Kuo (2017). Ranking indices determined using modified TOPSIS are superior to those attained using traditional TOPSIS when there are more than two alternatives, because modified TOPSIS considers the relative gaps of all alternatives and the weights of the distances from the PIS and NIS. Third, this study considered several objective functions (i.e., cost, delivery performance, product quality, and total utility) in constructing the MOLP model. We also included other critical factors such as real-world discounts, delivery risk, and product quality levels to increase the effectiveness of procurement planning. We also resolved the problem of counting cost twice in the MADM and MOLP models. Fourth, we applied an augmented max–min model in FMOLP to determine order quantity for each supplier. We transformed the fuzzy multi-objective model into a concise single-objective model by using an augmented max–min model, which achieved a superior utility value for each objective than the traditional max–min model.

According to the MADM results (Table 12), S_4 and S_1 achieved higher ranking indices (Table 12) in the evaluation. The final order allocations indicated that S_4 and S_1 also received higher procurement amounts, which demonstrated a high level of consistency. These results were confirmed by the subject firm's managers, who indicated that S_4 and S_1 have reputations for superior quality in the electronics industry. By contrast, S_2 achieved only the minimum procurement amount and did not achieve the minimum quantity required for a discount, resulting in a higher purchasing cost for the subject company. This supplier achieved a lower ranking than S_4 and S_1 due to its poor performance, despite having a higher unit price. In practice, the subject company might consider disqualifying S_2 as a supplier and transferring the procurement allocation to other suppliers. Therefore, S_2 should improve its evaluation performance to remain competitive in the market. The results demonstrate that the integrated model provides an effective reference for managers for selecting qualified suppliers and allocating orders to them.

We also compared the differences between the single order allocation model (only MODM model) and the proposed two-stage model (MADM and MODM model) (Table 17). The single order allocation model produces a higher utility value to each objective function than is the case with the two-stage evaluation model. However, the actual performance of the suppliers is not considered in the single order allocation model. For example, although the performance of supplier S_3 is worse than that of S_2, with the single allocation model it receives more procurements than S_2, which does not reflect company policy. In the proposed the model, S_3 procurement would be the lowest and would not exceed the discounted amount. Clearly, the proposed two-stage model is more practical and reliable, making the order allocation process more logical and reflective of supplier evaluation results.

/Please insert **Table 17** here/

Sensitivity analysis is carried out in order to examine the robustness of the model, as proposed by Prakash and Barua (2015) and Gupta and Barua (2017). We explore whether the criteria weight changes will affect supplier prioritization. When the highest criteria weight (product quality, C_{11}) changes from 0.1 to 0.9, the other criteria weights are adjusted in proportion. Following the modified fuzzy TOPSIS method to integrate supplier performance, we can observe the differences in supplier ranking. Table 18 shows the criteria weights for different values, with values of C_{11} ranging from 0.1 (lowest) to 0.9 (highest). The results of the sensitivity analysis are shown in Fig. 3. It can be seen that there is not much change in the ranking of the suppliers. Therefore, the robustness of the model is not significantly affected by changing the weight of a criterion. However, it is worth noting that when the weight of C_{11} is greater than 0.5, the rankings of S_2 and S_3 are exchanged.

/Please insert **Table 18** here/

/Please insert **Fig. 3** here/

In summary, the proposed integrated model provides a systematic approach for companies to select suppliers and decide on procurement plans in GSCM. Green purchasing is an issue of perception, and this efficient planning tool can reduce the subjectivity of managerial decision-making. The proposed model in academics has not been applied in GSCM. Our model integrates several state-of-the-art methods and considers various real-world factors, including the information uncertainty of industry decision-makers. Our study demonstrates the usefulness and effectiveness of the proposed model. It should bring several benefits to the case company: (i) determine the most suitable criteria for green supplier evaluation; (ii) reliable and effective evaluation of supplier performance; (iii) help procurement staff systematize the order allocation process. The cost of implementing the proposed model will include employee education, system integration and some changes to operational procedures. The biggest benefit will be the provision of a procurement decision support system which can reduce decision-making errors and management costs long-term.

In the future, researchers can expand on our research by using different MADM tools (e.g., VIKOR, PROMETHEE, ELECTRE, or grey relational analysis) to select suppliers or applying heuristic methods (e.g., nondominated sorting genetic algorithm II, the particle swarm optimization algorithm, or the ant colony optimization algorithm) to solve MOLP problems, and to compare the difference and applicability with current model. In addition, the group multiple criteria decision-making approach can be used to aggregate the opinions of experts from various backgrounds. If the company chooses to pursue different goals, the objective function can also be adjusted to make the model more practical to fulfill their changing needs.

Appendix A

This section introduces the BWM, modified fuzzy TOPSIS, and FMOLP methods, which we used in order allocation planning.

A.1. BWM

BWM derived the criteria weights from a pairwise comparison of the best and worst criteria, along with other criteria. The method by which BWM derived the criteria weights can be summarized as follows:

Step 1. Determining a set of dimensions and criteria for evaluating suppliers.

The experts identified *n* criteria that we used to calculate the weights.

Step 2. Determining best and worst criteria.

The experts selected the best (i.e., most appropriate, most preferred, or most crucial) criterion and worst (i.e., least acceptable, least preferred, or least crucial) criterion from those identified in *Step 1*.

Step 3. Obtaining best-to-others (BO) and others-to-worst (OW) vectors.

The experts assigned preference rankings of the best criterion over the other criteria on a scale of 1 to 9, with the more crucial criteria receiving a higher ranking and the less crucial criteria receiving a lower ranking. Similarly, the experts ranked the relative importance of the other criteria over the worst criteria. The resulting BO and OW vectors are expressed as follows:

$$V_b = \left(v_{b1}, v_{b2}, \ldots, v_{bn}\right)$$

$$V_w = \left(v_{1w}, v_{2w}, \ldots, v_{nw}\right)^T$$

where v_{bj} is the preference of the best criterion *b* over criterion *j*, and v_{jw} is the preference of criterion *j* over the worst criterion *w*. Clearly, $v_{bb},\ v_{ww} = 1$.

Step 4. Determining criteria weights: $\left(w_1^*, w_2^*, \ldots, w_n^*\right)$

The optimal weights were obtained using a linear programming model based on the BO and OW vectors. Minimized maximum absolute differences between

$\left|w_b - v_{bj} w_j\right|$ and $\left|w_j - v_{jw} w_w\right|$ indicated a minimized error distance; this principle was integrated into the following min–max model:

$$\min \max_j \left\{\left|w_b - v_{bj} w_j\right|, \left|w_j - v_{jw} w_w\right|\right\}$$

s. t.

$$\sum_j w_j = 1$$

$$w_j \geq 0 \text{, for all } j \tag{A1}$$

Eq. (A1) is a min–max objective function that can be converted into the following linear programming formulation:

$$\min \ \xi$$

s. t.

$$\left|w_b - v_{bj} w_j\right| \leq \xi \text{, for all } j$$

$$\left|w_j - v_{jw} w_w\right| \leq \xi \text{, for all } j$$

$$\sum_j w_j = 1$$

$$w_j \geq 0 \text{, for all } j \tag{A2}$$

Accordingly, Eq. (A2) generated the optimal weights $\left(w_1^*, w_2^*, \ldots, w_n^*\right)$ and optimal values of ξ (ξ^*); this equation is linear and has a unique solution. The model ensured high quality of the questionnaires by evaluating their consistency, and ξ^* is a critical parameter of the consistency test.

A.2. Modified fuzzy TOPSIS

The decision group consisted of p experts, each of whom had a fuzzy evaluation value that can be expressed as $\tilde{x}_{ijk} = \left(a_{ijk},\ b_{ijk},\ c_{ijk},\ d_{ijk}\right)$, i = 1, 2,..., m; j = 1, 2,..., n; k = 1, 2,..., p. Each expert k evaluated the performance of supplier i in j criteria. The method for integrating all expert fuzzy numbers $\tilde{x}_{ij}$ follows:

$$\tilde{x}_{ij} = \left(a_{ij},\ b_{ij},\ c_{ij},\ d_{ij}\right) \tag{A3}$$

where $a_{ij} = \min_k \left\{a_{ijk}\right\};\ b_{ij} = \frac{1}{p}\sum_{k=1}^{p} b_{ijk};\ c_{ij} = \frac{1}{p}\sum_{k=1}^{p} c_{ijk};\ d_{ij} = \max_k \left\{d_{ijk}\right\}$

We obtained the initial fuzzy matrix ($\tilde{D}$) from Eq. (A3):

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{A4}$$

The criteria can be divided into sets of benefit attributes (the larger the evaluation value, the better) and cost attributes (the smaller the evaluation value, the better). We normalized these data to maintain scale consistency of criteria, which the normalized fuzzy matrix ($\tilde{R}$) accomplished as follows:

$$\tilde{R} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \cdots & \tilde{r}_{1n} \\ \tilde{r}_{21} & \tilde{r}_{22} & \cdots & \tilde{r}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{r}_{m1} & \tilde{r}_{m2} & \cdots & \tilde{r}_{mn} \end{bmatrix} \tag{A5}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{d_j^*},\ \frac{b_{ij}}{d_j^*},\ \frac{c_{ij}}{d_j^*},\ \frac{d_{ij}}{d_j^*}\right),\ j \in B$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{a_{ij}},\ \frac{a_j^-}{b_{ij}},\ \frac{a_j^-}{c_{ij}},\ \frac{a_j^-}{d_{ij}}\right),\ j \in C$$

$$d_j^* = \max_i\ d_{ij},\ j \in B$$

$$a_j^- = \min_i\ a_{ij},\ j \in C$$

The benefit and cost attribute sets are denoted as B and C, respectively. The weighted normalized fuzzy matrix ($\tilde{V}$) was calculated as the product of the normalized fuzzy matrix ($\tilde{R}$) and criteria weights (w_j), as follows:

$$\tilde{V} = \begin{bmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \cdots & \tilde{v}_{1n} \\ \tilde{v}_{21} & \tilde{v}_{22} & \cdots & \tilde{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{m1} & \tilde{v}_{m2} & \cdots & \tilde{v}_{mn} \end{bmatrix} \tag{A6}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij}\left(\cdot\right) w_j$$

The weighted normalized fuzzy number is denoted as $\tilde{v}_{ij},\ \forall i, j$, and the FPIS ($\tilde{A}^*$) and FNIS ($\tilde{A}^-$) are defined as:

$$\tilde{A}^* = \left(\tilde{v}_1^*,\ \tilde{v}_2^*,\ldots,\tilde{v}_n^*\right) \tag{A7}$$

$$\tilde{A}^- = \left(\tilde{v}_1^-,\ \tilde{v}_2^-,\ldots,\tilde{v}_n^-\right) \tag{A8}$$

where $\begin{cases} \tilde{v}_j^* = \max\limits_i \left\{v_{ijk}\right\}, \\ \tilde{v}_j^- = \min\limits_i \left\{v_{ijk}\right\}, \end{cases} i = 1,\ 2,\ldots,\ m;\ j = 1,\ 2,\ldots,\ n$

Through fuzzy TOPSIS, the suppliers were ranked on the basis of distance, with the PIS distance for suppliers referred to as d^* and NIS distance referred to as d^-. The calculation is as follows:

$$d_i^* = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij},\ \tilde{v}_j^*\right) \tag{A9}$$

$$d_i^- = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij},\ \tilde{v}_j^-\right) \tag{A10}$$

Kuo (2017) proposed a modified TOPSIS ranking index that considers the NIS and PIS distance among all suppliers and remedies the shortcomings of traditional TOPSIS. The closeness coefficient (CC_i) is a reliable value that defines the standard for ranking suppliers (i.e., when the supplier performance is better, CC_i is greater). The formula is given by Eq. (A11):

$$CC_i = w^+ \left(d_i^- / \sum_{i=1}^{m} d_i^- \right) - w^- \left(d_i^* / \sum_{i=1}^{m} d_i^* \right),$$
$$\begin{cases} -1 \le CC_i \le 1 \\ 0 \le w^+ \le 1 \ , \ i = 1,\ 2,...,\ m \\ 0 \le w^- \le 1 \end{cases} \tag{A11}$$

In some situations, decision-makers have different preferences for NIS and PIS. Where w^+ and w^- represent the importance levels of NIS and PIS, $w^+ + w^- = 1$. According to Eq. (A11), when $\tilde{A}_i = \tilde{A}^*$, then $CC_i = 1$. By contrast, if $\tilde{A}_i = \tilde{A}^-$, then $CC_i = -1$. In other words, when CC_i is close to 1, the performance of supplier A_i is much closer to the FPIS and thus the supplier is highly ranked. However, if the value of CC_i is between -1 and 1, CC_i can be used for allocating orders but cannot be integrated into a multi-objective order allocation model. The fourth goal of FMOLP is to maximize the utility goal. The utility value should not be negative. Therefore, to standardize CC_i so that its value would range from 0 to 1, we applied Eq. (A12):

$$RC_i = \frac{1 + CC_i}{2},\ 0 \le RC_i \le 1,\ i = 1,\ 2,...,m \tag{A12}$$

We applied modified fuzzy TOPSIS evaluation values for each supplier (RC_i) to determine its ranking for order priority and to provide suggestions for improvement to poorly performing suppliers. Finally, we integrated the RC_i results into the multi-objective order allocation model to assist in executing subsequent purchasing plans.

A.3. FMOLP

This study applied FMOLP to establish an order allocation model. The process involved converting Eqs. (A13)-(A17) into a single-objective linear model, as follows:

$$\tilde{Z}_c = \sum_{c=1}^{C} c_{ci} x_i \le \tilde{Z}_c^0,\ c = 1,\ 2,...,\ C \tag{A13}$$

$$\tilde{Z}_p = \sum_{p=1}^{P} c_{pi} x_i \geq \tilde{Z}_p^0,\ p = C+1,\ldots,\ P \tag{A14}$$

s. t.

$$\tilde{g}_r(x) = \sum_{i=1}^{n} a_{ri} x_i \leq \tilde{b}_r,\ r = 1,\ 2,\ldots,\ R \tag{A15}$$

$$\sum_{i=1}^{n} a_{mi} x_i \leq b_m,\ m = R+1,\ldots,\ M \tag{A16}$$

$$x_i \geq 0,\ i = 1,\ 2,\ldots,\ n \tag{A17}$$

Eqs. (A13) and (A14) are minimum and maximum objective functions, referred to as $\tilde{Z}_c$ and $\tilde{Z}_p$. In Eqs. (A15)-(A17), $\tilde{g}_r(x)$ refers to fuzzy restriction. We obtained the positive optimal solution $Z_p^+ = \left(z_1^+, z_2^+, \ldots, z_P^+\right)$ and negative optimal solution $Z_p^- = \left(z_1^-, z_2^-, \ldots, z_P^-\right)$ for each objective. The result of each optimal solution was distinguished as an upper bound (positive optimal solution, Z_p^+) or lower bound (negative optimal solution, Z_p^-), as illustrated in the payoff table (Table A1).

/Please insert **Table A1** here/

$$\mu_c\left(Z_c\left(x\right)\right) = \begin{cases} 1, & \text{for } Z_c\left(x\right) \leq Z_c^+ \\ \dfrac{Z_c^- - Z_c\left(x\right)}{Z_c^- - Z_c^+}, & Z_c^+ \leq Z_c\left(x\right) \leq Z_c^-,\ c = 1,\ 2,\ldots,\ C \\ 0, & \text{for } Z_c\left(x\right) \geq Z_c^- \end{cases} \tag{A18}$$

$$\mu_p\left(Z_p\left(x\right)\right) = \begin{cases} 1, & \text{for } Z_p\left(x\right) \geq Z_p^+ \\ \dfrac{Z_p\left(x\right) - Z_p^-}{Z_p^+ - Z_p^-}, & Z_p^- \leq Z_p\left(x\right) \leq Z_p^+,\ p = C+1,\ 2,\ldots,\ P \\ 0, & \text{for } Z_p\left(x\right) \leq Z_p^- \end{cases} \tag{A19}$$

$$\mu_{gr}(x)=\begin{cases} 0, & \text{for } \sum_{i=1}^{n} a_{ri}x_i \le b_r - l_r \\ \dfrac{b_r\text{-}\sum_{i=1}^{n} a_{ri}x_i}{l_r}, & b_r - l_r \le \sum_{i=1}^{n} a_{ri}x_i \le b_r \\ \dfrac{\sum_{i=1}^{n} a_{ri}x_i\text{-}b_r}{u_r}, & b_r \le \sum_{i=1}^{n} a_{ri}x_i \le b_r + u_r \\ 0, & \text{for } \sum_{i=1}^{n} a_{ri}x_i \ge b_r + u_r \end{cases}, \begin{cases} r=1,2,\ldots,R \\ n=1,2,\ldots,N \end{cases} \tag{A20}$$

Eq. (A18) gives the membership function of minimization objectives, namely cost, delivery delay rate, defect ratio, and lead time. By contrast, Eq. (A19) is the membership function of maximization objectives, such as profit, benefit, service, and turnover rate. Eq. (A20) gives the linear membership function of the constraint formula.

This study applied an augmented max–min model proposed by Arikan (2013) that converts multiple objectives to a single objective, as given by Eq. (A21). The other constraints are given by Eqs. (A22)-(A27).

$$\max\ \lambda + \left\{ \sum_{q=1}^{S} \mu_q\left(c_q x\right) + \sum_{r=1}^{R} \mu_r\left(a_r x\right) \right\} \Big/ (S+R) \tag{A21}$$

s. t.

$$\lambda \le \mu_q\left(c_q x\right),\ q=1,\ 2,\ldots,\ S \tag{A22}$$

$$\lambda \le \mu_r\left(a_r x\right),\ r=1,\ 2,\ldots,\ R \tag{A23}$$

$$\mu_q\left(c_q x\right) \ge \alpha_q,\ q=1,\ 2,\ldots,\ S \tag{A24}$$

$$\mu_r\left(a_r x\right) \ge \alpha_r,\ r=1,\ 2,\ldots,\ R \tag{A25}$$

$$\sum_{i=1}^{n} a_{mi}x_i \le b_m,\ m=R+1,\ldots,\ M \tag{A26}$$

$$x \in X;\ \alpha_q,\ \alpha_r,\ \lambda \in [0,\ 1] \tag{A27}$$

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Figures

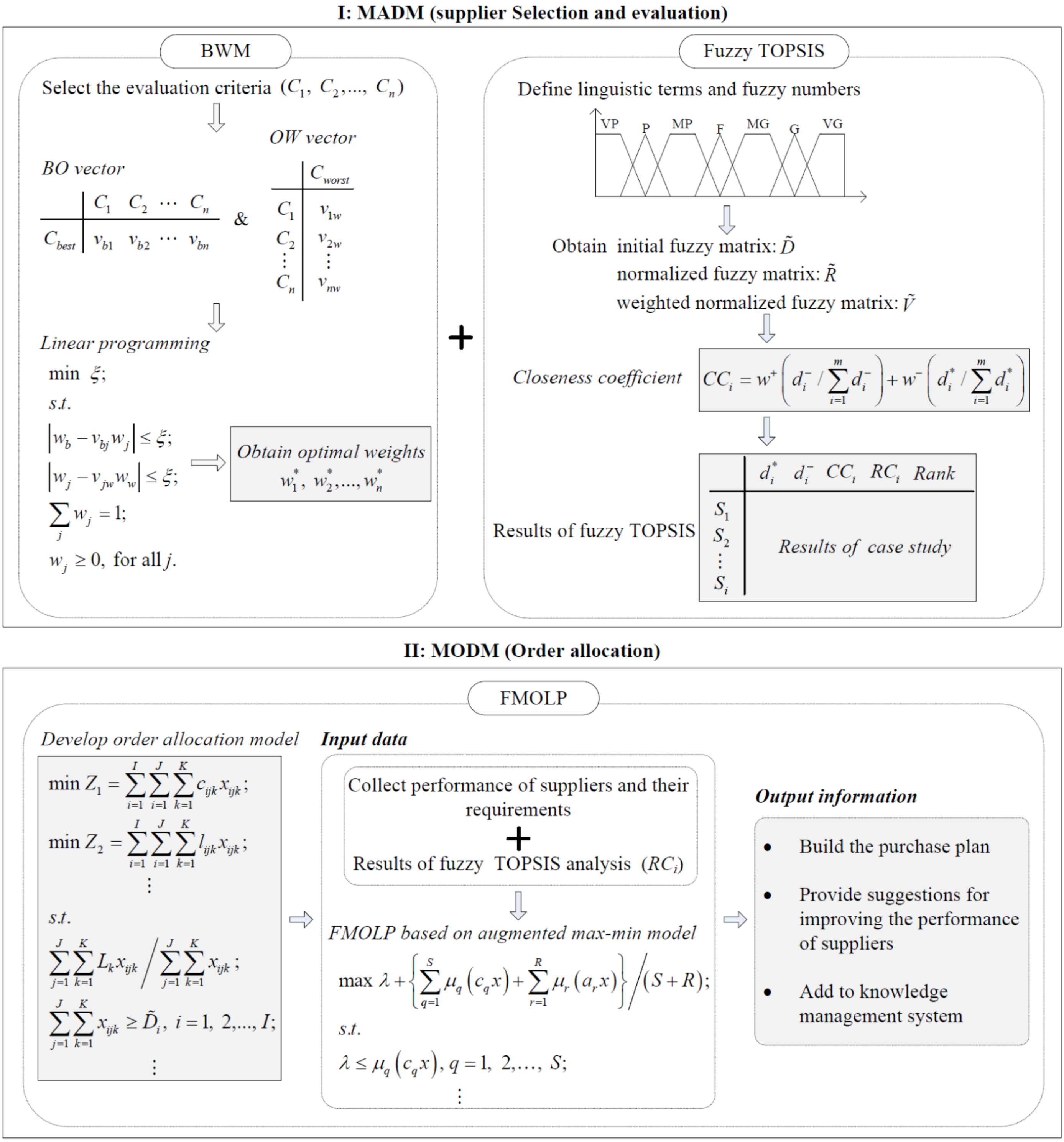

Fig. 1 Analytical procedure of this study

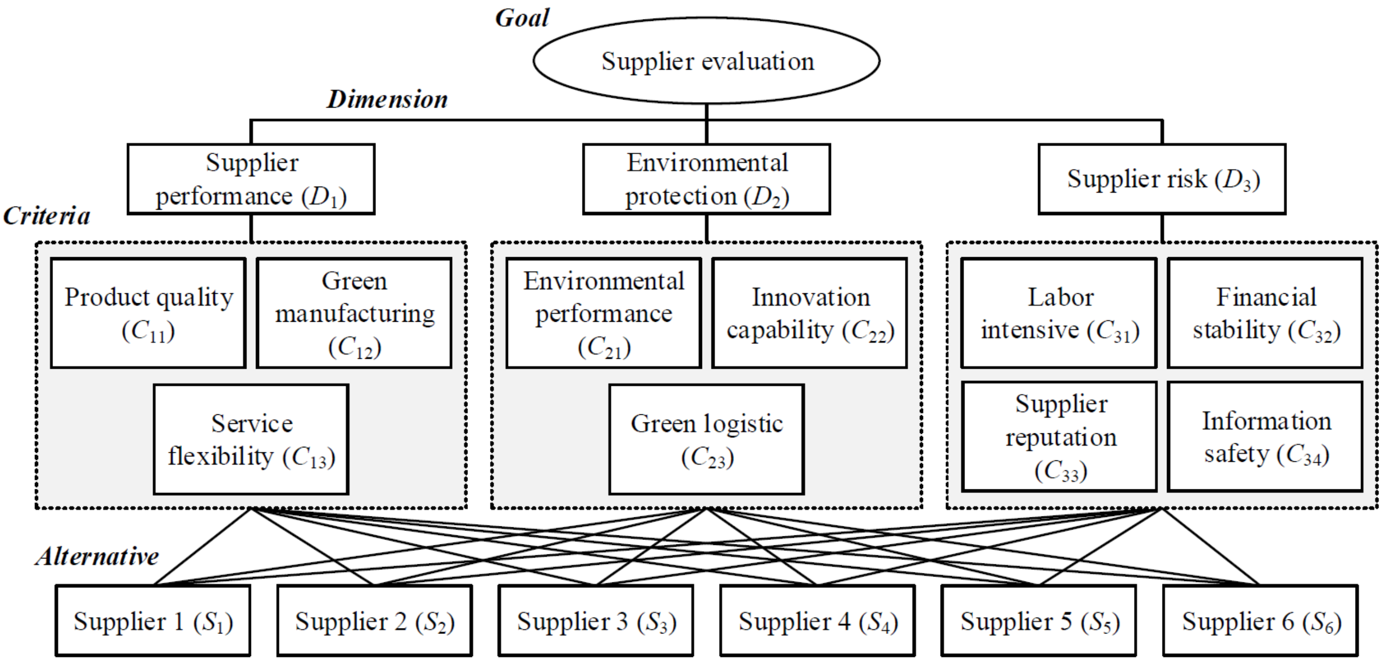

Fig. 2 Structure of green supplier evaluation

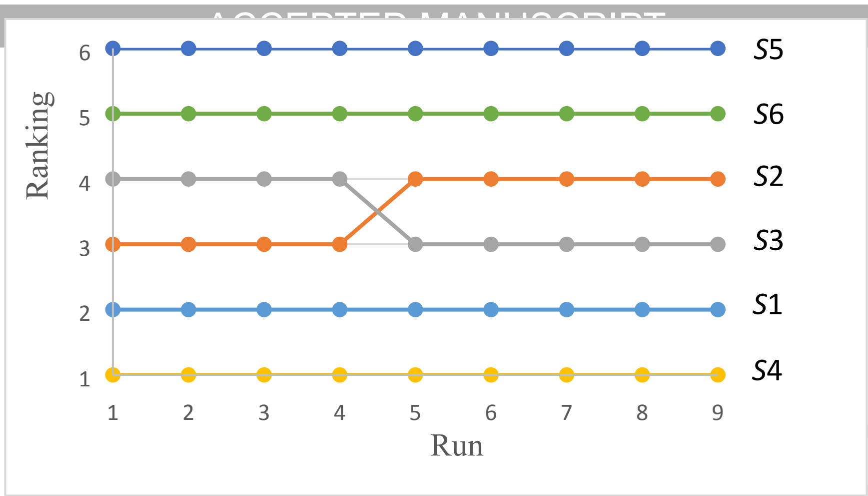

Fig. 3 Supplier ranking results after 9 runs in the sensitivity analysis

- This study integrates several state-of-the-art methods for solving problems in green supplier selection and order allocation.
- The integrated model combines the best–worst method, fuzzy TOPSIS, and fuzzy multi-objective linear programming.
- We demonstrated the proposed method using actual data provided by an electronics company.

Tables

Table 1 Summary of literature on integrating MADM and MODM for GSCM

Authors / year	Supplier selection method	Order allocation method
Lin et al. (2011)	ANP	Linear programming (LP)
Yeh and Chuang (2011)	—	Multi-objective genetic algorithm (MOGA)
Mafakheri et al. (2011)	AHP	Dynamic programming
Shaw et al. (2012)	Fuzzy AHP	Fuzzy multi-objective linear programming (FMOLP)
Zouggari and Benyoucef (2012)	Fuzzy AHP	Fuzzy TOPSIS
Kannan et al. (2013)	Fuzzy AHP and Fuzzy TOPSIS	Multi-objective linear programming (MOLP)
Govindan and Sivakumar (2016)	Fuzzy TOPSIS	Multi-objective linear programming (MOLP)
Hamdan and Jarndal (2017)	AHP	Multi-objective genetic algorithm (MOGA)
Hamdan and Cheaitou (2017a)	Fuzzy TOPSIS	AHP and multi-objective integer linear programming (MOILP)
Hamdan and Cheaitou (2017b)	Fuzzy TOPSIS and AHP	Weighted comprehensive criterion method and the branch-and-cut algorithm
Gören (2018)	DEMATEL and Taguchi loss functions	Bi-objective nixed integer programming
Park et al. (2018)	Multi-attribute utility theory (MAUT)	Multi-objective integer linear programming (MOILP)
Vahidi et al. (2018)	SWOT-QFD	Bi-objective programming and possibilistic-stochastic programming
Our proposed model	BWM and fuzzy TOPSIS	Fuzzy multi-objective linear programming (FMOLP) base on augmented max-min model

Table 2 Evaluation criteria for supplier selection

Dimension (D_i)	Criterion (C_{ij})	Definition	References
Supplier performance (D_1)	Product quality (C_{11})	Confirm product quality and provide relevant quality certificates, such as ISO 9000, QS9000, etc.	Kuo et al. (2010); Çebi and Otay (2016)
	Green manufacturing (C_{12})	Focus on clean and environmentally friendly production, and emphasize material recyclability.	Uygun and Dede (2016); Kuo and Lin (2011)
	Service flexibility (C_{13})	Level of service needed to meet customer demand, and when orders change can ensure fast delivery.	Kuo et al. (2010); Çebi and Otay (2016)
Environmental protection (D_2)	Environmental performance (C_{21})	Observe environmental regulations for products and reduce waste as much as possible. Supplier takes a pro-active approach to protecting the environment.	Uygun and Dede (2016); Kuo et al. (2010);
	Innovation capability (C_{22})	Innovative product design to ensure the product's disassembly, recyclability and sustainability.	Chen et al. (2012);
	Green logistic (C_{23})	Improve transport and logistics planning to effectively reduce pollution during transportation.	Uygun and Dede (2016); Çebi and Otay (2016)
Supplier risk (D_3)	Labor intensive (C_{31})	Supplier dependence on labor in production activities, considering staff productivity and turnover rate.	Rezaei et al. (2015); Govindan et al. (2015)
	Financial stability (C_{32})	Supplier's financial position and financial stability.	Kuo and Lin (2011)
	Supplier reputation (C_{33})	Supplier’s reputation in the industry, and past cooperation experience.	Govindan et al. (2015)
	Information safety (C_{34})	Supplier's information and communication capabilities in relation GSCM, confidentiality of confidence.	Chen et al. (2012); Govindan et al. (2015)

Table 3 BO vectors

Manager no.	*Best*	D_1	D_2	D_3
1	$\boldsymbol{D_2}$	2	1	4
2	$\boldsymbol{D_1}$	1	2	3
3	$\boldsymbol{D_1}$	1	5	3
4	$\boldsymbol{D_1}$	1	3	5
5	$\boldsymbol{D_1}$	1	2	3
6	$\boldsymbol{D_2}$	3	1	7
7	$\boldsymbol{D_1}$	1	2	5
8	$\boldsymbol{D_1}$	1	7	3

Table 4 OW vectors

Manager No.	1	2	3	4	5	6	7	8
Worst	$\boldsymbol{D_3}$	$\boldsymbol{D_3}$	$\boldsymbol{D_2}$	$\boldsymbol{D_3}$	$\boldsymbol{D_3}$	$\boldsymbol{D_3}$	$\boldsymbol{D_3}$	$\boldsymbol{D_2}$
D_1	3	3	5	5	3	5	5	7
D_2	4	2	1	3	2	7	3	1
D_3	1	1	3	1	1	1	1	5

Table 5 Dimension weights

	Manager No.								
Dimensions	1	2	3	4	5	6	7	8	Average
D_1	0.313	0.542	0.644	0.644	0.542	0.262	0.583	0.662	0.524
D_2	0.563	0.292	0.111	0.244	0.292	0.662	0.306	0.077	0.318
D_3	0.125	0.167	0.244	0.111	0.167	0.077	0.111	0.262	0.158
CR	0.038	0.042	0.039	0.039	0.042	0.033	0.012	0.033	0.035

Table 6 Criteria weights based on input from the eight experts

Dimension	Weight	Criteria	Local weight	Global weight	Rank
D_1	0.524	C_{11}	0.562	0.294	1
		C_{12}	0.207	0.109	4
		C_{13}	0.231	0.121	3
D_2	0.318	C_{21}	0.263	0.084	5
		C_{22}	0.507	0.161	2
		C_{23}	0.230	0.073	6
D_3	0.158	C_{31}	0.064	0.010	10
		C_{32}	0.463	0.073	7
		C_{33}	0.229	0.036	9
		C_{34}	0.244	0.039	8

Table 7 Linguistic terms and fuzzy numbers for supplier evaluation (Chen et al., 2006)

Linguistic terms	Codes	Fuzzy number
Very poor	VP	(0, 0, 1, 2)
Poor	P	(1, 2, 2, 3)
Medium poor	MP	(2, 3, 4, 5)
Fair	F	(4, 5, 5, 6)
Medium good	MG	(5, 6, 7, 8)
Good	G	(7, 8, 8, 9)
Very good	VG	(8, 9, 10, 10)

Table 8 Evaluation value for supplier 1 (S_1) from eight managers

Criteria	Manager no.							
	1	2	3	4	5	6	7	8
C_{11}	G	MG	G	MG	MG	VG	G	F
C_{12}	G	MG	G	MG	MG	F	F	MG
C_{13}	F	MG	G	MG	MP	MG	MG	MG
C_{21}	G	MG	G	MG	MG	G	G	MG
C_{22}	G	MG	G	MG	G	G	G	G
C_{23}	G	MG	G	VG	G	G	F	MG
C_{31}	MG	F	F	MP	MP	MG	P	MP
C_{32}	P	MP	MP	VP	MP	F	F	MP
C_{33}	MP	VP	G	MG	MG	G	MG	MG
C_{34}	MP	VP	G	MG	G	G	G	MG

Table 9 Initial fuzzy performance matrix ($\tilde{D}$)

	S_1	S_2	S_3	S_4	S_5	S_6
C_{11}	(4, 7, 7.5, 10)	(0, 2.63, 2.88, 6)	(2, 4.38, 5.25, 8)	(5, 8.5, 9.38, 10)	(0, 2.63, 2.88, 6)	(2, 4.38, 5.25, 8)
C_{12}	(4, 6.25, 6.75, 9)	(0, 3.13, 3.5, 8)	(2, 5.13, 5.63, 10)	(5, 8.5, 9.38, 10)	(0, 3.13, 3.5, 8)	(0, 3.13, 3.5, 8)
C_{13}	(2, 5.75, 6.5, 9)	(2, 4.75, 5.25, 1)	(0, 4, 4.5, 9)	(2, 8, 8.75,1)	(0, 4, 4.5, 9)	(2, 5.75, 6.5, 9)
C_{21}	(5, 7, 7.5, 9)	(7, 8.88, 9.75, 1)	(0, 2.38, 2.75, 6)	(2, 4.38, 5.25, 8)	(2, 4.38, 5.25, 8)	(0, 2.38, 2.75, 6)
C_{22}	(5, 7.5, 7.75, 9)	(7, 8.88, 9.75, 1)	(0, 3.13, 3.5, 6)	(2, 5.13, 6, 8)	(0, 3.13, 3.5, 6)	(0, 3.13, 3.5, 6)
C_{23}	(4, 7.25, 7.63, 10)	(0, 2.25, 2.88, 6)	(2, 4.38, 5.25, 8)	(5, 8.13, 9, 1)	(0, 2.25, 2.88, 6)	(2, 4.38, 5.25, 8)
C_{31}	(1, 4.13, 4.75, 8)	(4, 8.25, 8.88, 1)	(0, 2.25, 2.88, 6)	(2, 6.38, 7, 9)	(0, 2.25, 2.88, 6)	(2, 6.38, 7, 9)
C_{32}	(0, 3, 3.63, 6)	(2, 5.13, 5.63, 8)	(5, 7, 7.5, 9)	(7, 8.75, 9.5, 1)	(2, 5.13, 5.63, 8)	(0, 3, 3.63, 6)
C_{33}	(2, 6.13, 6.88, 9)	(0, 2.38, 3.13, 6)	(2, 5, 5.38, 8)	(7, 8.75, 9.5, 1)	(0, 2.38, 3.13, 6)	(2, 6.13, 6.88, 9)
C_{34}	(2, 6.63, 7.13, 9)	(0, 2, 2.75, 5)	(2, 5, 5.38, 8)	(7, 8.88, 9.75, 1)	(0, 2, 2.75, 5)	(2, 5, 5.38, 8)

Table 10 Normalized fuzzy matrix ($\tilde{R}$)

	S_1	S_2	S_3	S_4	S_5	S_6
C_{11}	(0.4, 0.7, 0.75, 1)	(0, 0.26, 0.29, 0.6)	(0.2, 0.44, 0.53, 0.8)	(0.5, 0.85, 0.94, 1)	(0, 0.26, 0.29, 0.6)	(0.2, 0.44, 0.53, 0.8)
C_{12}	(0.4, 0.63, 0.68, 0.9)	(0, 0.31, 0.35, 0.8)	(0.2, 0.51, 0.56, 1)	(0.5, 0.85, 0.94, 1)	(0, 0.31, 0.35, 0.8)	(0, 0.31, 0.35, 0.8)
C_{13}	(0.2, 0.58, 0.65, 0.9)	(0.2, 0.48, 0.53, 1)	(0, 0.4, 0.45, 0.9)	(0.2, 0.8, 0.88,1)	(0, 0.4, 0.45, 0.9)	(0.2, 0.58, 0.65, 0.9)
C_{21}	(0.5, 0.7, 0.75, 0.9)	(0.7, 0.89, 0.98, 1)	(0, 0.24, 0.28, 0.6)	(0.2, 0.44, 0.53, 0.8)	(0.2, 0.44, 0.53, 0.8)	(0, 0.24, 0.28, 0.6)
C_{22}	(0.5, 0.75, 0.78, 0.9)	(0.7, 0.89, 0.98, 1)	(0, 0.31, 0.35, 0.6)	(0.2, 0.51, 0.6, 0.8)	(0, 0.31, 0.35, 0.6)	(0, 0.31, 0.35, 0.6)
C_{23}	(0.4, 0.73, 0.76, 1)	(0, 0.23, 0.29, 0.6)	(0.2, 0.44, 0.53, 0.8)	(0.5, 0.81, 0.9, 1)	(0, 0.23, 0.29, 0.6)	(0.2, 0.44, 0.53, 0.8)
C_{31}	(0.1, 0.41, 0.48, 0.8)	(0.4, 0.83, 0.89, 1)	(0, 0.23, 0.29, 0.6)	(0.2, 0.64, 0.7, 0.9)	(0, 0.23, 0.29, 0.6)	(0.2, 0.64, 0.7, 0.9)
C_{32}	(0, 0.3, 0.36, 0.6)	(0.2, 0.51, 0.56, 0.8)	(0.5, 0.7, 0.75, 0.9)	(0.7, 0.88, 0.95, 1)	(0.2, 0.51, 0.56, 0.8)	(0, 0.3, 0.36, 0.6)
C_{33}	(0.2, 0.61, 0.69, 0.9)	(0, 0.24, 0.31, 0.6)	(0.2, 0.5, 0.54, 0.8)	(0.7, 0.88, 0.95, 1)	(0, 0.24, 0.31, 0.6)	(0.2, 0.61, 0.69, 0.9)
C_{34}	(0.2, 0.66, 0.71, 0.9)	(0, 0.2, 0.28, 0.5)	(0.2, 0.5, 0.54, 0.8)	(0.7, 0.89, 0.98, 1)	(0, 0.2, 0.28, 0.5)	(0.2, 0.5, 0.54, 0.8)

Table 11 Weighted normalized fuzzy matrix ($\tilde{V}$)

	S_1	S_2	S_3	S_4	S_5	S_6
C_{11}	(0.12, 0.21, 0.22 ,0.29)	(0, 0.08, 0.09, 0.18)	(0.06, 0.13, 0.16, 0.24)	(0.15, 0.25, 0.28, 0.29)	(0, 0.08, 0.09, 0.18)	(0.06, 0.13, 0.16, 0.24)
C_{12}	(0.04, 0.07, 0.07, 0.1)	(0, 0.03, 0.04, 0.09)	(0.02, 0.06, 0.06, 0.11)	(0.05, 0.09, 0.10, 0.11)	(0, 0.03, 0.04, 0.09)	(0, 0.03, 0.04, 0.09)
C_{13}	(0.02, 0.07, 0.08, 0.11)	(0.02, 0.06, 0.06, 0.12)	(0, 0.05, 0.05, 0.11)	(0.02, 0.1, 0.11, 0.12)	(0, 0.05, 0.05, 0.11)	(0.02, 0.07, 0.08, 0.11)
C_{21}	(0.04, 0.06, 0.06, 0.08)	(0.06, 0.07, 0.08, 0.08)	(0, 0.02, 0.02, 0.05)	(0.02, 0.04, 0.04, 0.07)	(0.02, 0.04, 0.04, 0.07)	(0, 0.02, 0.02, 0.05)
C_{22}	(0.08, 0.12, 0.13, 0.15)	(0.11, 0.14, 0.16, 0.16)	(0, 0.05, 0.06, 0.1)	(0.03, 0.08, 0.1, 0.13)	(0, 0.05, 0.06, 0.1)	(0, 0.05, 0.06, 0.1)
C_{23}	(0.03, 0.05, 0.06, 0.07)	(0, 0.02, 0.02, 0.04)	(0.02, 0.03, 0.04, 0.06)	(0.04, 0.06, 0.07, 0.07)	(0, 0.02, 0.02, 0.04)	(0.02, 0.03, 0.04, 0.06)
C_{31}	(0, 0, 0.01, 0.01)	(0, 0.01, 0.01, 0.01)	(0, 0, 0, 0.01)	(0, 0.01, 0.01, 0.01)	(0, 0, 0, 0.01)	(0, 0.01, 0.01, 0.01)
C_{32}	(0, 0.02, 0.03, 0.04)	(0.02, 0.04, 0.04, 0.06)	(0.04, 0.05, 0.06, 0.07)	(0.05, 0.06, 0.07, 0.07)	(0.02, 0.04, 0.04, 0.06)	(0, 0.02, 0.03, 0.04)
C_{33}	(0.01, 0.02, 0.03, 0.03)	(0, 0.01, 0.01, 0.02)	(0.01, 0.02, 0.02, 0.03)	(0.03, 0.03, 0.03, 0.04)	(0, 0.01, 0.01, 0.02)	(0.01, 0.02, 0.02, 0.03)
C_{34}	(0.01, 0.03, 0.03, 0.04)	(0, 0.01, 0.01, 0.02)	(0.01, 0.02, 0.02, 0.03)	(0.03, 0.03, 0.04, 0.04)	(0, 0.01, 0.01, 0.02)	(0.01, 0.02, 0.02, 0.03)

Table 12 Fuzzy TOPSIS calculation results and ranking

	d_i*	d_i^-	CC_i	RC_i	Rank
S_1	0.402	0.687	0.037	0.518	2
S_2	0.552	0.550	-0.007	0.497	3
S_3	0.587	0.520	-0.017	0.492	4
S_4	0.335	0.770	0.059	0.530	1
S_5	0.693	0.422	-0.048	0.476	6
S_6	0.611	0.494	-0.024	0.488	5

Table 13 Supplier production data

	S_1	S_2	S_3	S_4
RC_i	0.514	0.481	0.473	0.532
Capacity limit	8500	9000	9500	10000
Defect rate	2.3%	2%	2.5%	1.8%
Delay delivery rate	2.2%	3.5%	2.5%	3%
Quantity discount	Q ≥ 5000	Q ≥ 5500	Q ≥ 5800	Q ≥ 6500
Unit cost (dollar)	28.5 (26.5)	30 (27.5)	32 (28)	28 (26)
Production lead time (day)	4 (6)	6 (7)	4 (5)	5 (6)

**Demand limit of company*

Total demand of product = $\widetilde{26000}$ = (25500, 26000, 27000)

Average number of lead days = $\tilde{6}$ = (5, 6, 7)

Table 14 Notation and definition of parameters

Indices	
i	Index of product i, i=1, 2, …, I
j	Price level of product j, j=1, 2, …, J
k	Supplier k, k=1, 2, …, K
Variables	
x_{ijk}	A mount of product i purchased from supplier k at price level j
y_{ijk}	= 1, if supplier k is selected for product i at price level j ($x_{ijk} > 0$); = 0, otherwise ($x_{ijk} = 0$)
Parameters	
D_i	Demand of product i
$\overline{L}_i$	Product i average lead time
L_k	Lead time of supplier k
c_{ijk}	The price of product i offered by supplier k at price level
l_k	Delay delivery rate of supplier k
d_k	Defect rate of supplier k
w_k	Overall RC_i of supplier k obtained by fuzzy TOPSIS
C_{ik}	Supplier k maximum capacity limit for product i
V_{ik}	Quantity discount minimum order quantity of product i from Supplier k

Table 15 Payoff table for multi-objective functions

	Z_1	Z_2	Z_3	Z_4
Z^+	677750	649.5	509.5	13777.5
Z^-	766143	815.0	613.0	12420.5
$Z^+ - Z^-$	-88393	-165.5	-103.5	1357

Table 16 Results of order allocation model

Decision variables	
S_1	$y_{11} = 0$, $[x_{11} = 0]$; $y_{21} = 1$, $[x_{21} = 8500]$
S_2	$y_{12} = 0$, $[x_{12} = 0]$; $y_{22} = 1$, $[x_{22} = 5500]$
S_3	$y_{13} = 1$, $[x_{13} = 2753]$; $y_{23} = 0$, $[x_{23} = 0]$
S_4	$y_{14} = 0$, $[x_{14} = 0]$; $y_{24} = 1$, $[x_{24} = 9247]$
Utility of objective function and constraints	
λ_1	0.692
λ_2	0.539
λ_3	0.698
λ_4	0.601
λ_d	1
λ_l	1
Objective compromise solution	
Z_1	705018
Z_2	725.735
Z_3	540.771
Z_4	13236.073

Table 17 Results of order allocation model

	Our proposed order allocation model	The order allocation without considering supplier evaluation results
Decision variables		
S_1	$y_{11} = 0$, $[x_{11} = 0]$; $y_{21} = 1$, $[x_{21} = 8500]$	$y_{11} = 0$, $[x_{11} = 0]$; $y_{21} = 1$, $[x_{21} = 7088]$
S_2	$y_{12} = 0$, $[x_{12} = 0]$; $y_{22} = 1$, $[x_{22} = 5500]$	$y_{12} = 0$, $[x_{12} = 0]$; $y_{22} = 1$, $[x_{22} = 5794]$
S_3	$y_{13} = 1$, $[x_{13} = 2753]$; $y_{23} = 0$, $[x_{23} = 0]$	$y_{13} = 0$, $[x_{13} = 0]$; $y_{23} = 1$, $[x_{23} = 5800]$
S_4	$y_{14} = 0$, $[x_{14} = 0]$; $y_{24} = 1$, $[x_{24} = 9247]$	$y_{14} = 0$, $[x_{14} = 0]$; $y_{24} = 1$, $[x_{24} = 7318]$
Utility of objective function and constraints		
λ_1	0.692	0.75
λ_2	0.539	0.698
λ_3	0.698	0.906
λ_4	0.601	-
λ_d	1	1
λ_l	1	1
Objective compromise solution		
Z_1	705018	699835
Z_2	725.735	723.266
Z_3	540.771	555.628
Z_4	13236.073	-

Table 18 All the criteria weights change according to C_{11}

Criteria	BWM weight	1	2	3	4	5	6	7	8	9
C_{11}	0.294	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
C_{12}	0.109	0.138	0.123	0.108	0.092	0.077	0.062	0.046	0.031	0.015
C_{13}	0.121	0.154	0.137	0.120	0.103	0.086	0.069	0.051	0.034	0.017
C_{21}	0.084	0.107	0.095	0.083	0.071	0.059	0.047	0.036	0.024	0.012
C_{22}	0.161	0.206	0.183	0.160	0.137	0.114	0.091	0.069	0.046	0.023
C_{23}	0.073	0.093	0.083	0.073	0.062	0.052	0.042	0.031	0.021	0.010
C_{31}	0.010	0.013	0.011	0.010	0.009	0.007	0.006	0.004	0.003	0.001
C_{32}	0.073	0.093	0.083	0.073	0.062	0.052	0.041	0.031	0.021	0.010
C_{33}	0.036	0.046	0.041	0.036	0.031	0.026	0.021	0.015	0.010	0.005
C_{34}	0.038	0.049	0.044	0.038	0.033	0.027	0.022	0.016	0.011	0.005
Total	1	1	1	1	1	1	1	1	1	1

Table A1 Payoff table for multi-objective decision-making

	f_1 (maximize)	f_2 (minimize)		f_p (maximize)
Z^+	$\max f_1(x)$	$\min f_2(x)$	$\cdots$	$\max f_p(x)$
Z^-	$\min f_1(x)$	$\max f_2(x)$	$\cdots$	$\min f_p(x)$