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A Fuzzy Group Decision-making-based Method for Green Supplier Selection and Order Allocation

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A Fuzzy Group Decision-making-based Method for Green Supplier Selection and Order Allocation

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Abstract： With the intensity of market competitiveness, the worsening of the global environment, and the improvement of public concern about environmental protection, the issue of green purchasing has received considerable attention. The vast majority of existing studies on green purchasing have concentrated on supplier selection with green criteria, so as to realize sustainable operations, whereas it is more feasible and economical for businesses to obtain the proper products from adaptable and suitable suppliers at the right times, rates, and volumes, which is referred to as supplier selection and order allocation. *To resolve the aforementioned two crucial challenges*, *we propose a group decision-making method within an ambiguous context*. *A fuzzy ranking approach based on the technique for order of preference by similarity to ideal solution and analytic hierarchy process (TOPSIS-AHP) is addressed*. *The proposed solution enables each of the green and classical criteria to be given a flexible preference under the organization's strategy. Supplier ranks are utilized in a bi-objective optimization model to allocate orders*, *where the procurement performance is maximized while the entire procurement cost is minimized*. The findings show that the proposed method is capable of assessing the performance of providers and optimizing the distribution of orders among candidate suppliers.

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基于模糊群决策的绿色供应商选择和订单分配方法

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摘要：随着市场竞争愈发激烈、全球环境日益恶化以及公众环保意识的提高，绿色采购问题受到了广泛关注。现有研究绝大多数聚焦于考虑绿色准则的供应商选择问题，以实现可持续经营。然而，在综合考虑时间、价格和成本等因素的前提下，从适应性强的供应商处获得适当的产品，对于企业来说更为可行和经济，即供应商选择和订单分配。*为了解决上述关键问题，提出了一种模糊环境下的多准则群体决策方法。提出了一种基于理想解相似性偏好排序和层次分析法(technique for order of preference by similarity to ideal solution and analytic hierarchy process，TOPSIS-AHP)的*

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模糊排序方法，该方法可根据企业战略灵活调整传统准则和绿色准则的权重。在双目标优化模型中引入供应商排名进行订货，在实现采购绩效最大化的同时，最大限度地降低采购成本。结果表明：所提方法能够有效评价供应商绩效，并优化候选供应商之间的订单分配。

关键词：供应商选择；订单分配；模糊群决策；technique for order of preference by similarity to ideal solution and analytic hierarchy process(TOPSIS-AHP)；双目标优化

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0 Introduction

Supply chain management (SCM) covers all procedures that convert raw materials into final products, in effect controlling the flow of items and services. It enables companies to reduce unnecessary expenditures and accelerate the delivery of goods to customers. Recently, purchasing has been thought of as a key factor that has a considerable impact on SCM. Especially in the mechanical equipment operation scenario, spare parts must be purchased in advance to ensure a normal and continuous production process with less downtime. In practice, the company usually makes spare part procurement plans and maintenance schedules according to the remaining life of machinery equipment[1-2]. The procedure of procurement includes deciding which specific suppliers to choose and how much to order from them. Choosing the proper suppliers helps to reduce the cost of material purchases and thus makes firms more competitive[3]. In general, there are several factors to consider when choosing suppliers, such as price, technical level, quality, and delivery time. Therefore, supplier selection is also a type of multi-criteria decision-making (MCDM) process that deals with multiple competing factors while making decisions[4-5]. Dickson[6] summarized 23 factors considered by purchasing managers while solving supplier selection issues. In recent years, as companies become more environmentally conscious, and they need to reduce carbon emissions, the concept of green supplier selection has emerged and is rapidly gaining popularity[7-8]. A set of green criteria, such as material waste reduction, recyclable resource usage, and eco-design, is employed to evaluate potential suppliers across the green supplier selection process[9-11]. In terms of order allocation, a common strategy is to determine the ideal quantities to be ordered from available vendors during a specific scheduling period through purchasing specialists. To realize optimization objectives considering time-varying prices, capacities, demands, and discount factors, researchers have developed several mathematical programming approaches[12-15]. Although many studies concerning supplier selection issues and order allocation problems have been reported, little work has been devoted to the two challenges simultaneously, especially in the fuzzy group decision-making scenario.

This paper proposes a unified framework for green supplier selection and order allocation problems, where a single-product and multi-phase procurement scenario with certain demand, variable number of suppliers, and numerous volume discounts are considered. The developed method is composed of three stages. First, by utilizing the fuzzy technique for order of preference by similarity to ideal solution (TOPSIS) and both sets of conventional and green criteria, decision-makers calculate preference weights for each vendor. Specifically, the conventional criteria include cost, quality, and reliability. The supplier's environmental credentials and shipping method are involved in the green standards. In the fuzzy TOPSIS approach, triangular fuzzy numbers (TFNs) are employed to indicate the fuzziness that affects the decision-maker's assessment. After that, the top level of the organization utilizes the AHP method to measure the relative significance of conventional and green criteria in the organization's strategy. The previous performance weights combined with the relative significance comprise the final weights for each provider. This works flexibly when identifying potential vendors even though the green criterion set is given high priority. A supplier who performs well on traditional criteria but poorly in terms of green standards may not be included as an optimal supplier. Finally, the aggregated performance weights of the providers are input into a bi-objective optimization model which lowers both variable and fixed expenses while maximizing the value of the selected vendors. The weighted comprehensive criterion method (WCCM) is also employed as the solution approach. The main contributions of this paper can be summarized as follows.

(1) This study aims to take a holistic view of both supplier selection and order allocation issues in a fuzzy group decision-making scenario, so as to provide an integrated solution for green purchasing.

(2) We present a fuzzy TOPSIS method to determine the preference weights of suppliers and employ the group AHP approach to assign weights to traditional and green criteria. The fusion of fuzzy TOPSIS and AHP allows the purchaser to flexibly evaluate the candidate suppliers based on the company's strategy.

(3) We design a bi-objective order allocation model that takes into account several factors such as variable number of suppliers, multi-stage discounts, inventory, and shortages. The optimization goal of this model is to minimize the total cost of procurement while maximizing the procurement value.

(4) The effectiveness of the proposed method is verified through a case study, and some sensitivity analyses are investigated.

1 Supplier ranking using fuzzy TOPSIS and AHP methods

Fig. 1 depicts the flowchart of the proposed framework. The first step is to apply the fuzzy TOPSIS and AHP methods to rank suppliers. The goal of the generic MCDM issue is to assess the available alternatives $\boldsymbol{A}_i (i=1,2,\cdots,I)$ in light of several criteria $\boldsymbol{C}_j (j=1,2,\cdots,J)$. The candidate alternatives, e. g., suppliers, should be rated by professional decision-makers. Herein, $\boldsymbol{C}_j$ is a collection of properties, and it symbolizes the elements influencing decision-makers' choices while considering alternatives $\boldsymbol{A}_i$. s_{ij} represents the rating score of alternative $\boldsymbol{A}_i$ concerning criterion $\boldsymbol{C}_j$, and α_j represents the weighting of $\boldsymbol{C}_j$. The matrix form for an MCDM issue is formulated as

$$\boldsymbol{D}=\begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1J} \\ s_{21} & s_{22} & \cdots & s_{2J} \\ \vdots & \vdots & \cdots & \vdots \\ s_{I1} & s_{I2} & \cdots & s_{IJ} \end{bmatrix}$$

$$\boldsymbol{C}_j=[s_{1j}, s_{2j}, \cdots, s_{Ij}]^{\mathrm{T}}$$

$$\boldsymbol{A}_i=[s_{i1}, s_{i2}, \cdots, s_{iJ}]$$

$$\boldsymbol{R}=[\alpha_1, \alpha_2, \cdots, \alpha_J]$$

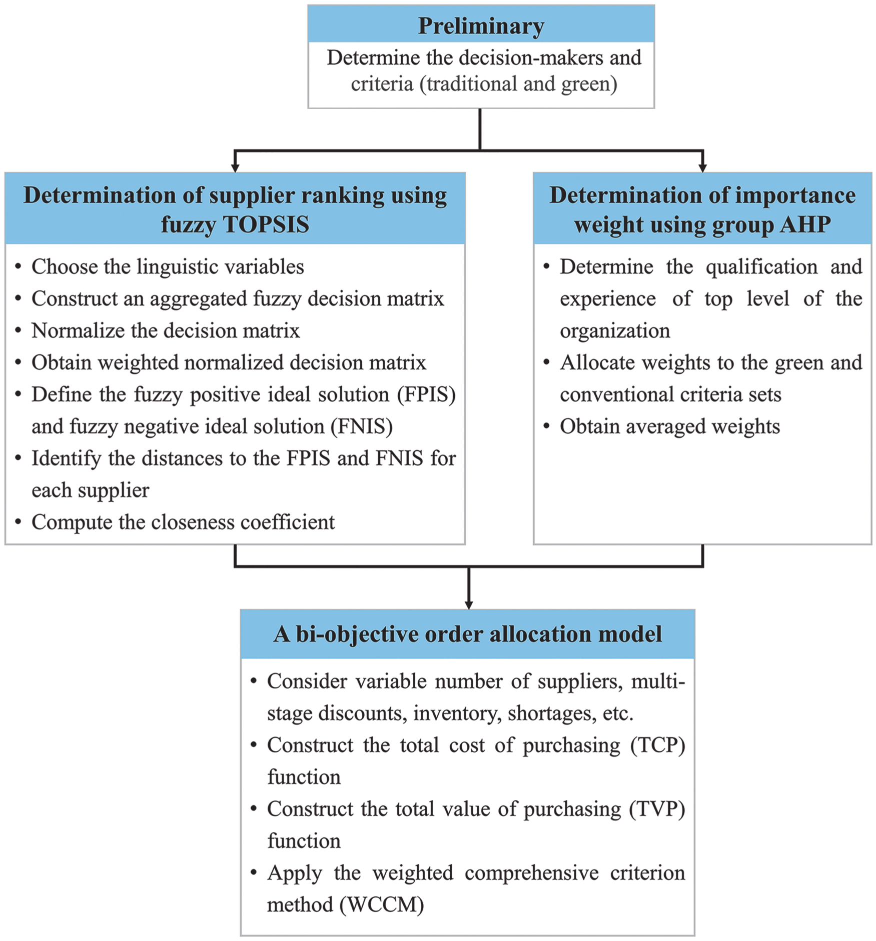

Fig. 1 Flowchart of proposed approach

In conventional MCDM strategies, the ratings and the weightings for criteria are explicitly offered with numerical values. Hwang et al.[16] first developed the well-known MCDM method, i. e., the TOPSIS method. According to the definition of TOPSIS, the favored alternative should be the one that is both farthest from the negative ideal solution (NIS) and nearest to the positive ideal solution (PIS), where numerical performance ratings and criteria weights are included.

1.1 Fuzzy TOPSIS

In some cases, real-world data may contain ambiguities and uncertainties that may not be accurately expressed by traditional precise values. For example, human judgments, particularly preferences, are sometimes imprecise, and an accurate quantitative representation of individual decisions is hard to generate. In order to deal with inexact numerical quantities practically, employing language evaluations rather than specific numbers may be a more reasonable method, namely, replacing the numerical ratings and criteria weights with linguistic variables[17-18]. Inspired by this, we develop a fuzzy decision-making strategy, which takes into account multi-person and multi-criteria conditions and extends the original TOPSIS idea. Given the uncertainty in the group decision manner, it makes sense to apply the linguistic variables to assess the importance of standards and rank each candidate in relation to each

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standard. The first step in the process of fuzzy TOPSIS is to collect the fuzzy scores of the decision-makers, and then a fuzzy decision matrix and its weighted normalized form are constructed. Afterwards, we clarify the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) with a distance formula defined in advance. At last, the ranking order is established using the closeness coefficient of each option. As the option is closer to FPIS while also being further away from FNIS, the closeness coefficient is greater.

1.1.1 Triangular fuzzy number

A variable with a word as its value is referred to as the linguistic variable. Because linguistic variables are sufficiently straightforward to be expressed as fuzzy integers, we employ them in our study to reflect the ambiguity during the procedure for making decisions. Many types of linguistic scales have been recommended for TFN with various points. We employ the seven-point linguistic measure in this study. Descriptions of the scales for the criteria and alternatives are provided in Tables 1~2, respectively. The evaluations of the options and the priority ascribed to the various criteria are considered linguistic factors in this study. Tables 1~2 illustrate these linguistic variables with positive-triangular fuzzy numbers.

Table 1 Linguistic variables for the significance of each standard

Linguistic variable	TFN
Very low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium high (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1.0)
Very high (VH)	(0.9, 1.0, 1.0)

Table 2 Linguistic variables for the rating of alternatives

Linguistic variable	TFN
Very poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very good (VG)	(9, 10, 10)

1.1.2 Calculation procedure

It is assumed that a group of N experts utilize various linguistic variables to denote the criterion importance and alternative ratings. The following phases describe the entire process.

Step 1: Each decision maker subjectively rates the options and assesses the importance weight of each criterion relative to others. The average weights of the criteria and the ratings of the alternatives can be derived from the following formula:

$$\tilde{s}_{ij}=\frac{\tilde{s}_{ij}^{1}+\tilde{s}_{ij}^{2}+\cdots+\tilde{s}_{ij}^{N}}{N}$$

$$\tilde{\alpha}_{j}=\frac{\tilde{\alpha}_{j}^{1}+\tilde{\alpha}_{j}^{2}+\cdots+\tilde{\alpha}_{j}^{N}}{N}$$

where $\tilde{s}_{ij}^{N}$ and $\tilde{\alpha}_{j}^{N}$ represent the rating score of alternative $\boldsymbol{A}_i$ with respect to criterion $\boldsymbol{C}_j$ and significance weight of criterion $\boldsymbol{C}_j$ provided by the Nth expert. $\tilde{s}_{ij}$ and $\tilde{\alpha}_j (i=1,2,\cdots,I;\ j=1,2,\cdots,J)$ are presented by linguistic variables. TFNs are employed to describe these linguistic variables: $\tilde{s}_{ij}=(x_{ij},y_{ij},z_{ij})$ and $\tilde{\alpha}_j=(\alpha_{j1},\alpha_{j2},\alpha_{j3})$.

Step 2: Construct an aggregated fuzzy decision matrix as

$$\tilde{\boldsymbol{D}}=\begin{bmatrix}\tilde{s}_{11} & \tilde{s}_{12} & \dots & \tilde{s}_{1J}\\ \tilde{s}_{21} & \tilde{s}_{22} & \dots & \tilde{s}_{2J}\\ \vdots & \vdots & & \vdots\\ \tilde{s}_{I1} & \tilde{s}_{I2} & \dots & \tilde{s}_{IJ}\end{bmatrix}$$

$$\boldsymbol{R}=[\tilde{\alpha}_1,\tilde{\alpha}_2,\cdots,\tilde{\alpha}_J]$$

Step 3: Convert multiple standard scales into similar scales by utilizing a linear scale conversion

$$\tilde{n}_{ij}=\begin{cases}\left(\dfrac{x_{ij}}{z_j^+},\dfrac{y_{ij}}{z_j^+},\dfrac{z_{ij}}{z_j^+}\right),\ \boldsymbol{C}_j \text{ is a benefit criterion}\\ \left(\dfrac{x_j^-}{z_{ij}},\dfrac{x_j^-}{y_{ij}},\dfrac{x_j^-}{x_{ij}}\right),\ \boldsymbol{C}_j \text{ is a cost criterion}\end{cases}$$

$$z_j^+=\max_i z_{ij}$$

$$x_j^-=\min_i x_{ij}$$

The normalizing approach assures that the TFNs fall within [0, 1].

Step 4: Using the criterion weight $\tilde{\alpha}_j$ multiplied by $\tilde{n}_{ij}$, we derive the weighted normalized decision matrix $\tilde{u}_{ij}$.

$$\tilde{u}_{ij}=\tilde{n}_{ij}\times\tilde{\alpha}_j$$

Step 5: Define the FPIS (A^+) and FNIS (A^-) as

$$A^+=[\tilde{u}_1^+,\tilde{u}_2^+,\cdots,\tilde{u}_J^+]=[(1,1,1),(1,1,1),\cdots,(1,1,1)]$$

$$A^-=[\tilde{u}_1^-,\tilde{u}_2^-,\cdots,\tilde{u}_J^-]=[(0,0,0),(0,0,0),\cdots,(0,0,0)]$$

Step 6: Identify the distances to the FPIS and FNIS for every option

$$d_i^+=\sum_{j=1}^{J}d(\tilde{u}_{ij},\tilde{u}_j^+),\ i=1,2,\cdots,I$$

$$d_i^-=\sum_{j=1}^{J}d(\tilde{u}_{ij},\tilde{u}_j^-),\ i=1,2,\cdots,I$$

where $d(\cdot,\cdot)$ represents the distance from one number to another. For example, when two triangular fuzzy numbers $\tilde{p}=(x_1,y_1,z_1)$ and $\tilde{q}=(x_2,y_2,z_2)$ are given, the distance between them can be written as

$$d(\tilde{p},\tilde{q}):=\left[\frac{(x_1-x_2)^2+(y_1-y_2)^2+(z_1-z_2)^2}{3}\right]^{1/2}$$

Step 7: Compute the closeness coefficient CC_i.

$$CC_i=\frac{d_i^-}{d_i^++d_i^-},\quad i=1,2,\cdots,I$$

As CC_i approaches 1, the alternative $\boldsymbol{A}_i$ moves away from the FNIS and toward the FPIS. Thus, we can apply CC_i to prioritize the ranking of all options, enabling us to select the ideal solution.

1.2 AHP

In this paper, we employ AHP to determine the weights of the traditional and green criteria subsets. Saaty[19] developed the AHP for making decisions in the 1970 s. Based on this tool, the decision-makers evaluate the candidates in terms of the extent to which they meet the criteria and evaluate the importance of the criteria in achieving the objectives. These evaluations work with a scale of weighting[20], enabling the qualitative information quantified and improving decision-making efficiency. Table 3 illustrates the common AHP pairwise comparison scale.

Table 3 Pairwise comparison scale

Intensity of importance	Definition
1	Equally important
3	Moderately important
5	Very important
7	Strongly important
9	Extremely important
2, 4, 6, 8	Intermediate values

In the proposed framework, AHP method is applied to allocate weights to the green and conventional criteria sets according to the company' s strategy, and it is assumed that more than one manager participates in the weighting process. According to the concept of collaboration, collective decision-making tends to be more effective and helps to reduce risk compared with individual decision-making. It is assumed that a total of M managers are involved. The mth manager provides the weight vector as

$$\beta^m=(\beta_{\mathrm{G}}^m,\beta_{\mathrm{T}}^m)$$

To integrate the total weight vectors from a group of managers and obtain the averaged weight vector, we apply the following formulas:

$$\bar{\beta}_{\mathrm{G}}=\prod_{m=1}^{M}(\beta_{\mathrm{G}}^{m})^{\lambda_m}$$

$$\bar{\beta}_{\mathrm{T}}=\prod_{m=1}^{M}(\beta_{\mathrm{T}}^{m})^{\lambda_m}$$

$$\beta_{\mathrm{G}}=\frac{\bar{\beta}_{\mathrm{G}}}{\bar{\beta}_{\mathrm{G}}+\bar{\beta}_{\mathrm{T}}} \tag{1}$$

$$\beta_{\mathrm{T}}=\frac{\bar{\beta}_{\mathrm{T}}}{\bar{\beta}_{\mathrm{G}}+\bar{\beta}_{\mathrm{T}}} \tag{2}$$

subject to

$$\sum_{m=1}^{M}\lambda_m=1$$

where λ_m denotes the coefficient of the *m*thmanager, which is determined by the qualification and experience. Eq. (1) and Eq. (2) are designed to ensure that the sum of the two weights is 1.

2 A bi-objective order allocation model

In our order allocation model, two objective functions constitute the bi-objective optimization paradigm. The first expression intends to maximize the overall performance of the chosen providers, which is determined by the criteria preference weights, candidate rankings, and item quantity. The second function attempts to reduce the entire purchasing expenses, which includes the constant ordering fees, changeable unit cost, holding of stock cost, and penalty shortage cost. Moreover, the factor of volume discounts is considered for each supplier. Different quantities of items ordered from a single supplier correspond to different order unit prices. For each provider, the model determines just one type of unit pricing and its related range of needed quantities. The model permits variation in provider availability throughout the various planning horizon intervals.

2.1 Notations

2.1.1 Parameters

T: Phases in scheduling.

n_t: The entire number of providers accessible during phase t; $t=1, 2, \cdots, T$.

V_i: The full quantity of volume discount interval for supplier i; $i=1, 2, \cdots, n_t$.

w_{G}: Weighting of green criteria set acquired via AHP.

w_{T}: Weighting of conventional criteria set acquired via AHP.

GC_{it}: Closeness coefficient of vendor i during phase t obtained in the case of the green criteria; $i=1, 2, \cdots, n_t$ and $t=1, 2, \cdots, T$.

TC_{it}: Closeness coefficient of vendor i during phase t obtained in the case of the conventional criteria.

UC_{iv}: Price per unit for vendor i, $i=1, 2, \cdots, n_t$ matching the volume discount range v;$v=1, 2, \cdots, V_i$.

FC_{it}: Fixed ordering cost for vendor i during phase t; $t=1, 2, \cdots, T$.

H_t: Holding cost per item during t; $t=1, 2, \cdots, T$.

S_t: Penalty shortage cost per item during t and $t=1, 2, \cdots, T$.

$C_{itv}^{\min}$: Minimum amount offered by provider i during phase t for the volume discount range v. When $v=1$, $C_{it1}^{\min}$ indicates the typical lowest order size from supplier i in phase t.

$C_{itv}^{\max}$: Maximum amount offered by provider i during phase t for the volume discount range v. When $v=V_i$, $C_{itVi}^{\max}$indicates the typical maximum order size from supplier i in phase t.

D_t: Demand during t; $t=1, 2, \cdots, T$.

M^{S}, M^{H}: Large positive values that are assumed to be the same as the entire demand across the planning period in this model.

S^S, S^H: Small positive integers that are equivalent to 0.5 in this model.

2.1.2 Decision variables

Q_{itv}: Quantity provided by vendor i, $i=1, 2, \cdots, n_t$ during t, $t=1, 2, \cdots, T$ and to be bought within the volume discount interval v and $v=1, 2, \cdots, V_i$.

Y_{itv}: A binary parameter indicating whether the order quantity offered by vendor i, $i=1, 2, \cdots, n_t$ during t, $t=1, 2, \cdots, T$ falls into the volume discount interval v, $v=1, 2, \cdots, V_i$ or not.

I_t^H: Inventory level after phase t and $t=1, 2, \cdots, T$.

I_t^S: A status parameter which is negative and represents the quantity of unmet requirements (shortage) after phase t; $t=1, 2, \cdots, T$.

Y_t^H: A binary value indicating the inventory state after phase t. $Y_t^H=1$ demonstrates that inventory quantity is positive, and vice versa.

Y_t^S: A binary value indicating whether the inventory amount is negative after phase t. $Y_t^S=1$ demonstrates that inventory quantity is negative, and vice versa.

2.2 Bi-objective integer linear optimization model

Herein, we introduce a bi-objective integer linear programming (BOILP) model to investigate the supplier selection and order allocation problem while accounting for inventory backlog. Additionally, the model considers multiple discounting strategies and a variable number of suppliers over time, which increases the complexity of the problem. The detailed objective functions and constraints are presented below.

$$\max TVP=\beta_G\times TGVP+\beta_T\times TTVP \tag{3}$$

$$\min TCP=\sum_{t=1}^{T}\sum_{i=1}^{n_t}\sum_{v=1}^{V_i}(UC_{iv}\times Q_{itv}+FC_{it}\times Y_{itv}+H_t\times I_t^H-S_t\times I_t^S) \tag{4}$$

with

$$TGVP=\sum_{t=1}^{T}\sum_{i=1}^{n_t}\sum_{v=1}^{V_i}GC_{it}\times Q_{itv}$$

$$TTVP=\sum_{t=1}^{T}\sum_{i=1}^{n_t}\sum_{v=1}^{V_i}TC_{it}\times Q_{itv}$$

subject to

$$Y_{itv}C_{itv}^{\min}\leqslant Q_{itv}\leqslant Y_{itv}C_{itv}^{\max} \tag{5}$$

$$I_{t-1}^H+I_{t-1}^S+\sum_{i=1}^{n_t}\sum_{v=1}^{V_i}Q_{itv}-I_t^H-I_t^S=D_t \tag{6}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{n_t}\sum_{v=1}^{V_i}Q_{itv}+I_0=\sum_{t=1}^{T}D_t \tag{7}$$

$$-M^SY_t^S\leqslant I_t^S\leqslant -S^SY_t^S \tag{8}$$

$$S^HY_t^H\leqslant I_t^H\leqslant M^HY_t^H \tag{9}$$

$$Y_t^H+Y_t^S\leqslant 1 \tag{10}$$

$$\sum_{v=1}^{V_i}Y_{itv}\leqslant 1 \tag{11}$$

$$Q_{itv}, I_t^H, I_t^S\in \mathrm{Z} \tag{12}$$

$$Y_{itv}, Y_t^H, Y_t^S\in\{0, 1\} \tag{13}$$

for

$$\forall i=1,2,\cdots,n_t,\ \forall t=1,2,\cdots,T,\ \ \forall v=1,2,\cdots,V_i$$

Eq. (3) optimizes the total value of purchasing (TVP), which comprises the total green value of purchasing (TGVP) and the total traditional value of purchasing (TTVP). It contains the preferences assigned to the vendors, the number of items provided by the suppliers, and the weights of the conventional and green criteria sets. Eq. (4) minimizes the total cost of purchasing (TCP) in all phases within the range of prices offered by the supplier, including the variable, fixed, inventory holding, and penalty shortfall costs. Eq. (5) guarantees that the amount provided by every supplier i during phase t meets the requirements of the discount price interval between $C_{itv}^{\min}$ and $C_{itv}^{\max}$.

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Additionally, $C_{it1}^{\min}$ indicates the lowest order quantity permitted by a provider. If the sales management strategy of supplier i lacks the lowest order size, $C_{it1}^{\min}$ is assumed to be 0, and ordering negative numbers is prohibited. Eq. (6) makes sure that the need would be met by the order size, the inventory on hand, or by designating a shortage. Eq. (7) guarantees that, although not always occurring at the same moment, the whole demand over the full planned horizon is met. Eq. (8) confirms that if I_t^{S} is negative, the relevant binary variable Y_t^{S} equals 1. Eq. (9) makes sure that when I_t^{H} is positive, Y_t^{H} becomes 1. The suggested approach considers scarcity and backlog. However, by setting M^{S} equal to zero and eliminating constraint (7), the lost sales can be handled with ease. Eq. (10) ensures that each period chooses only one inventory type, either positive and negative, or none of the two inventory types. According to Eq. (11), each provider has a maximum range chosen for each period. Eq. (12) ensures that the decision variables are all integers, while the binary natures of Y_{itv}, Y_t^{H}, and Y_t^{S} are guaranteed by Eq. (13).

2.3 Solution approach

Since WCCM[21-22] is easy to use and very efficient in terms of the number of Pareto solutions, it has been widely used to deal with bi-objective models. This strategy employs normalization to combine objective functions with various ranges into a single objective function. Specifically, in order to determine the best values, $TVP_{\max}$ and $TCP_{\min}$, WCCM first resolves two single-objective functions independently while adhering to the limitations of the original models. The two objective functions are then multiplied by a weight and combined into a single objective function problem. The goal of this problem is to minimize the sum of the relative changes from optimal values in each objective function. We compute the relative variation (normalization) as follows:

$$f_1 = (TVP_{\max} - TVP)/TVP_{\max}$$

$$f_2 = (TCP - TCP_{\min})/TCP_{\min}$$

Subsequently, we combine these normalized functions by allocating the weight to them and minimize a single objective function as follows:

$$\min f = \omega_1 f_1 + \omega_2 f_2 \tag{14}$$

It should be noted that altering the weight factors may result in various Pareto optimum solutions.

3 Numerical example

The proposed approach is experimentally validated using a numerical example. Firstly, the fuzzy TOPSIS method is utilized to determine the weight assignment between each provider under the conventional and green criteria. AHP is then conducted by the corporate leadership. Next, we apply WCCM to the bi-objective optimization problem. Finally, we conduct some comparative experiments to investigate the effect of different parameter combinations on the value of the objective function. As shown in Table 4, the ordering costs differ among the four suppliers and vary over time. In addition, the demand, holding cost, and shortage cost also change over time, which depend on the actual situation of the purchaser. Meanwhile, owing to the intricate nature of the supply chain, the suppliers available are inconsistent from period to period. Table 5 summarizes the supplier data and model parameters. As described in Section 2.1, various suppliers offer diverse volume discounts whenever the ordering quantity reaches a particular threshold. Tables 6~9 illustrate the price discounts of the four suppliers.

Table 4 Ordering costs for all suppliers over time

Supplier	1st phase	2nd phase	3rd phase	4th phase
1	2 792	2 923	2 718	2 953
2	2 602	2 589	2 655	2 990
3	2 645	2 615	2 962	2 719
4	2 730	2 585	2 715	2 555

Table 5 Demand, holding cost, shortage cost, and available suppliers in the planning horizon

Phase	Demand	Holding cost	Shortage cost	Available Suppliers
1	1 750	4	8	S1, S2, S3, S4
2	1 800	4	9	S1, S2, S3
3	1 765	3	8	S2, S3
4	1 630	5	8	S1, S2, S4

Table 6 Volume discount schedule for supplier 1

Min quantity	Price	Max quantity
0	35.0	119
120	32.7	239
240	30.4	359
360	28.0	479
480	25.8	599

Table 7 Volume discount schedule for supplier 2

Min quantity	Price	Max quantity
0	34	84
85	33	169
170	31	254
255	30.5	339
340	29	424
425	28	509
510	27	594
595	26	679
680	25	764
765	24	849

Table 8 Volume discount schedule for supplier 3

Min quantity	Price	Max quantity
0	35.0	74
75	33.8	149
150	32.7	224
225	31.6	299
300	30.5	374
375	29.4	449
450	28.3	530

Table 9 Volume discount schedule for supplier 4

Min quantity	Price	Max quantity
0	33.0	119
120	30.4	239
240	27.8	359
360	25.3	479
480	22.7	599

3.1 Alternatives ranking

The ranking of alternatives has a critical impact on the overall framework, as it is both the result of the expert's evaluation of suppliers and an input in the order allocation model. By employing the idea of fuzzy TOPSIS, we determine the closeness coefficient of each supplier. The relevance weights for the traditional and green criteria are decided by senior management using AHP. It is assumed that there are three decision makers, four available suppliers, three traditional criteria, and three green criteria. Table 10 lists the ratings, where TC stands for a kind of traditional criterion; GC is a type of green criterion, and the criterion with an asterisk (*) denotes a negative criterion (cost or lead time). The significance of the criterion is evaluated by linguistic variables shown in Table 11.

Table 10 Alternative evaluation according to traditional and green criteria

		TC1*	TC2	TC3	GC1	GC2	GC3
DM1	S1	G	G	F	VG	F	VG
	S2	G	VG	VG	VG	VG	F
	S3	VG	F	G	MG	G	G
	S4	VG	P	G	MG	G	MG
DM2	S1	VG	MG	MG	G	F	MG
	S2	MG	VG	MG	VG	MG	F
	S3	G	G	MG	VG	G	VG
	S4	G	VP	G	MG	F	G
DM3	S1	MG	F	F	VG	MP	MG
	S2	MG	VG	G	VG	G	MG
	S3	MG	G	MG	MG	MG	VG
	S4	G	MP	G	VG	MG	MG

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Table 11 Evaluation of traditional and green criteria

	TC1*	TC2	TC3	GC1	GC2	GC3
DM1	MH	VH	M	VH	M	H
DM2	VH	H	H	VH	MH	VH
DM3	MH	VH	H	VH	MH	VH

To explore the effect of different TOPSIS methods on the closeness coefficient, we demonstrate four fuzzy TOPSIS methods denoted as Case A, Case B, Case C, and Case D. The differences between them mainly lie in the calculations of Steps 1 and 5 in Section 1.1.2, namely, the aggregation of group rating and weights and the definitions of FPIS and FNIS. Table 12 details the four approaches.

The closeness coefficients for all vendors based on both conventional and green criteria are shown in Table 13. Meanwhile, we illustrate the graphical results of closeness coefficients across Case A to Case D, as shown in Figs. 2~3.

Table 12 Differences between four fuzzy TOPSIS methods

	Case A	Case B	Case C	Case D
Aggregated fuzzy rating	$x_{ij}=\frac{1}{N}\sum_{n=1}^{N}x_{ij}^{n}$ $y_{ij}=\frac{1}{N}\sum_{n=1}^{N}y_{ij}^{n}$ $z_{ij}=\frac{1}{N}\sum_{n=1}^{N}z_{ij}^{n}$	$x_{ij}=\frac{1}{N}\sum_{n=1}^{N}x_{ij}^{n}$ $y_{ij}=\frac{1}{N}\sum_{n=1}^{N}y_{ij}^{n}$ $z_{ij}=\frac{1}{N}\sum_{n=1}^{N}z_{ij}^{n}$	$x_{ij}=\min_{n}x_{ij}^{n}$ $y_{ij}=\frac{1}{N}\sum_{n=1}^{N}y_{ij}^{n}$ $z_{ij}=\max_{n}z_{ij}^{n}$	$x_{ij}=\min_{n}x_{ij}^{n}$ $y_{ij}=\frac{1}{N}\sum_{n=1}^{N}y_{ij}^{n}$ $z_{ij}=\max_{n}z_{ij}^{n}$
Aggregated fuzzy weight	$\alpha_{j1}=\frac{1}{N}\sum_{n=1}^{n}\alpha_{j1}^{n}$ $\alpha_{j2}=\frac{1}{N}\sum_{n=1}^{n}\alpha_{j2}^{n}$ $\alpha_{j3}=\frac{1}{N}\sum_{n=1}^{n}\alpha_{j3}^{n}$	$\alpha_{j1}=\frac{1}{N}\sum_{n=1}^{n}\alpha_{j1}^{n}$ $\alpha_{j2}=\frac{1}{N}\sum_{n=1}^{n}\alpha_{j2}^{n}$ $\alpha_{j3}=\frac{1}{N}\sum_{n=1}^{n}\alpha_{j3}^{n}$	$\alpha_{j1}=\min_{n}\alpha_{j1}^{n}$ $\alpha_{j2}=\frac{1}{N}\sum_{n=1}^{N}\alpha_{j2}^{n}$ $\alpha_{j3}=\max_{n}\alpha_{j3}^{n}$	$\alpha_{j1}=\min_{n}\alpha_{j1}^{n}$ $\alpha_{j2}=\frac{1}{N}\sum_{n=1}^{N}\alpha_{j2}^{n}$ $\alpha_{j3}=\max_{n}\alpha_{j3}^{n}$
FPIS	$\tilde{u}_{j}^{+}=(1,1,1)$	$\tilde{u}_{j}^{+}=\max_{i}(u_{ij1},u_{ij2},u_{ij3})$	$\tilde{u}_{j}^{+}=(1,1,1)$	$\tilde{u}_{j}^{+}=\max_{i}(u_{ij1},u_{ij2},u_{ij3})$
FNIS	$\tilde{u}_{j}^{-}=(0,0,0)$	$\tilde{u}_{j}^{-}=\min_{i}(u_{ij1},u_{ij2},u_{ij3})$	$\tilde{u}_{j}^{-}=(0,0,0)$	$\tilde{u}_{j}^{-}=\min_{i}(u_{ij1},u_{ij2},u_{ij3})$

Table 13 Closeness coefficients of traditional and green criteria in Cases A~D

		Case A	Case B	Case C	Case D
Traditional criteria	Supplier 1	0.543	0.481	0.541	0.549
	Supplier 2	0.698	0.980	0.642	0.964
	Supplier 3	0.598	0.647	0.569	0.665
	Supplier 4	0.446	0.195	0.446	0.170
Green criteria	Supplier 1	0.636	0.445	0.603	0.398
	Supplier 2	0.661	0.565	0.645	0.625
	Supplier 3	0.702	0.741	0.650	0.669
	Supplier 4	0.633	0.431	0.608	0.430

As can be seen in Fig. 2, the rankings of the suppliers under the four cases are consistent; however, the difference in the closeness coefficients among the four suppliers is more pronounced in Cases B and D. This is reflected in the degree of irregularity of the polygon in the radar chart. A more irregular polygon indicates a greater difference in closeness coefficients. By reviewing the formulas of Cases B and D, it can be noticed that they are different from Cases A and C in terms of FPIS and FNIS, which are related to the normalized decision matrix rather than being kept constant, e.g., (1, 1, 1) or (0, 0, 0), which would affect the calculation of the closeness coefficients. It can also be observed from Fig. 3 that Supplier 2 and Supplier 3 are ranked higher in four cases. The closeness coefficients of the four suppliers under Case B and Case D are more discriminative than those of Case A and Case C.

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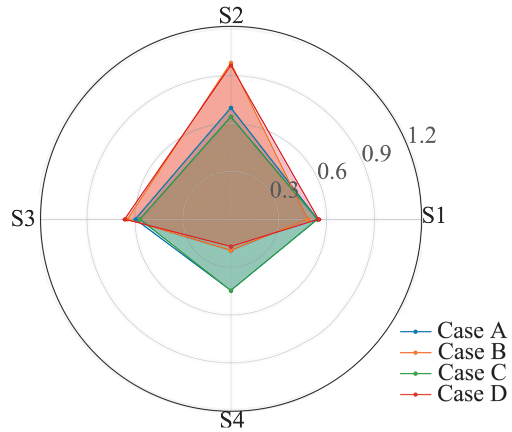

Fig. 2 Radar chart of suppliers' *CC* under traditional criteria

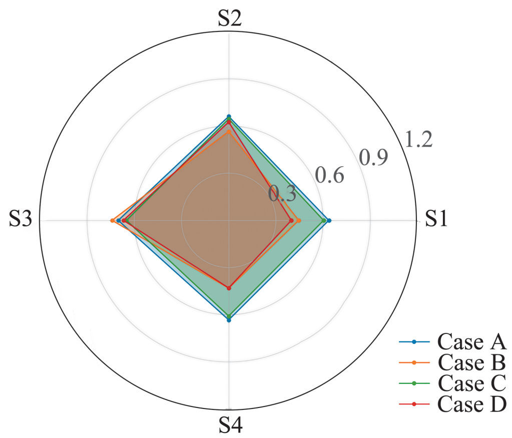

Fig. 3 Radar chart of suppliers' *CC* under green criteria

3.2 Impact of criteria weights

Since β_G and β_T are involved in the formula of TVP, we discuss different weight settings and obtain the optimal TVP values across Case A to Case D. Tables 14~17 list the ideal TVP solutions in four cases for a change in β_G/β_T from 0.2/0.8 to 0.8/0.2. Five variations of ω_1/ω_2 are considered here to better explore the effect of β_G/β_T on optimal TVP.

From Tables 14~17, it can be observed that in any case and under any ω_1/ω_2, the value of TVP monotonically increases or decreases with the change of β_G/β_T. Moreover, in each case, no matter how ω_1/ω_2 changes, the direction of TVP change is the same, or in other words, the monotonicity of TVP is independent of ω_1/ω_2. The visualization results of TVP values in Case A and Case D are illustrated in Fig. 4 and Fig. 5. As can be seen from Fig. 4, in Case A, the value of TVP gradually becomes larger with increasing β_G, regardless of the change in ω_1/ω_2. In Case D, on the contrary, the value of TVP gets progressively smaller as β_G increases, as shown in Fig. 5.

Table 14 Optimal TVP values in Case A with various criteria weights β_G/β_T under different weight factors ω_1/ω_2

ω_1/ω_2	β_G/β_T			
	0.2/0.8	0.4/0.6	0.6/0.4	0.8/0.2
0.1/0.9	4 280.660	4 350.212	4 419.763	4 489.315
0.3/0.7	4 322.240	4 383.435	4 444.630	4 505.825
0.5/0.5	4 387.232	4 411.947	4 474.198	4 536.449
0.7/0.3	4 416.676	4 440.459	4 498.614	4 541.553
0.9/0.1	4 416.676	4 464.100	4 511.525	4 558.949

Table 15 Optimal TVP values in Case B with various criteria weights β_G/β_T under different weight factors ω_1/ω_2

ω_1/ω_2	β_G/β_T			
	0.2/0.8	0.4/0.6	0.6/0.4	0.8/0.2
0.1/0.9	4 703.152	4 474.735	4 246.319	4 020.128
0.3/0.7	4 906.480	4 664.431	4 363.439	4 147.502
0.5/0.5	4 995.489	4 738.221	4 441.903	4 201.934
0.7/0.3	4 995.489	4 738.221	4 480.953	4 223.685
0.9/0.1	4 995.489	4 738.221	4 480.953	4 223.685

Table 16 Optimal TVP values in Case C with various criteria weights β_G/β_T under different weight factors ω_1/ω_2

ω_1/ω_2	β_G/β_T			
	0.2/0.8	0.4/0.6	0.6/0.4	0.8/0.2
0.1/0.9	4 074.115	4 149.426	4 224.738	4 300.049
0.3/0.7	4 107.040	4 176.199	4 241.639	4 311.608
0.5/0.5	4 158.304	4 176.199	4 245.359	4 335.254
0.7/0.3	4 184.698	4 219.687	4 281.071	4 335.254
0.9/0.1	4 184.698	4 240.025	4 295.353	4 345.910

Table 17 Optimal TVP values in Case D with various criteria weights β_G/β_T under different weight factors ω_1/ω_2

ω_1/ω_2	β_G/β_T			
	0.2/0.8	0.4/0.6	0.6/0.4	0.8/0.2
0.1/0.9	4 751.198	4 524.612	4 298.025	4 056.929
0.3/0.7	4 964.222	4 713.060	4 398.345	4 186.639
0.5/0.5	5 070.365	4 795.543	4 478.617	4 205.839
0.7/0.3	5 070.365	4 795.543	4 520.720	4 229.935
0.9/0.1	5 070.365	4 795.543	4 520.720	4 245.898

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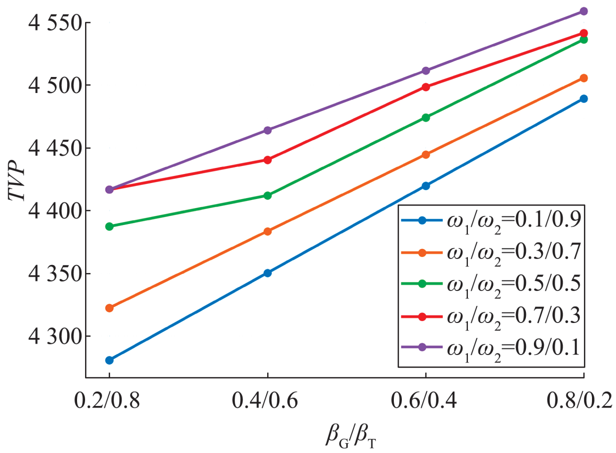

Fig. 4 TVP values in Case A under different weight settings

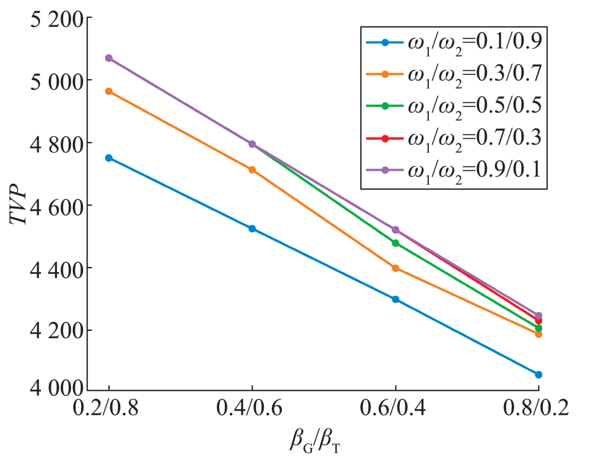

Fig. 5 TVP values in Case D under different weight settings

In order to understand the cause of this phenomenon, we first propose a synthetic criterion (SC) that integrates the green criterion and the traditional criterion and study the closeness coefficient of the SC written as follows:

$$SC=\beta_G\times GC+\beta_T\times TC$$

The values of the closeness coefficients for SC under Case A and Case D are presented in Tables 18 and 19. These tables list the SC closeness coefficients for each supplier under each β_G/β_T, as well as the sum of the coefficient values for all suppliers. It is not difficult to see that the variation of these total values with β_G/β_T is consistent with the variation of optimal TVP values with β_G/β_T. Therefore, it can be concluded that the change of the optimal value of TVP is jointly influenced by β_G/β_T, *GC*, and *TC*.

Table 18 Closeness coefficients of SC in Case A

Supplier	β_G/β_T			
	0.2/0.8	0.4/0.6	0.6/0.4	0.8/0.2
1	0.561 6	0.580 2	0.598 8	0.617 4
2	0.690 6	0.683 2	0.675 8	0.668 4
3	0.618 8	0.639 6	0.660 4	0.681 2
4	0.483 4	0.520 8	0.558 2	0.595 6
Sum	2.354 4	2.423 8	2.493 2	2.562 6

Table 19 Closeness coefficients of SC in Case D

Supplier	β_G/β_T			
	0.2/0.8	0.4/0.6	0.6/0.4	0.8/0.2
1	0.518 8	0.488 6	0.458 4	0.428 2
2	0.896 2	0.828 4	0.760 6	0.692 8
3	0.665 8	0.666 6	0.667 4	0.668 2
4	0.222 0	0.274 0	0.326 0	0.378 0
Sum	2.302 8	2.257 6	2.212 4	2.167 2

3.3 Analysis of Pareto set

The Pareto set, also known as the Pareto frontier or Pareto boundary, is a concept in economics and decision theory that represents the set of all optimal outcomes for a multi-objective optimization problem. It involves a collection of solutions in which no individual objective can be improved without worsening at least one other objective. In other words, the Pareto set illustrates the trade-offs between different objectives, and the solutions on the Pareto frontier are considered the best possible outcomes given the set of objectives and constraints. Tables 20~23 show the ideal solutions for Cases A~D with various combinations of ω_1/ω_2 after adjusting β_G/β_T. It can be seen that the optimal TCP and TVP values for all four cases all monotonically increase as ω_1 increases. Moreover, it can be observed from Fig. 6 that the optimal TCP and TVP values are positively correlated, which indicates that the solutions with varying ω_1/ω_2 are Pareto set. It means that higher

TVP and lower TCP cannot be obtained at the same time. A larger ω_2 helps lower the TCP value, whereas it will inevitably result in a smaller TVP value. On the contrary, a larger ω_1 contributes to improving the purchasing performance, which will also increase the cost. As a coefficient related to TVP, larger ω_1 indicates a higher proportion of TVP in the optimization function, and thus higher TVP is obtained. Similarly, a larger ω_2 facilitates the TCP optimization process, i. e., lower TCP values. Therefore, in practice, the emphasis on TCP and TVP can be adjusted by changing the ω_1 and ω_2.

Table 20 Optimal TCP and TVP values with β_G/β_T = 0.2/0.8

ω_1/ω_2	Case A		Case B		Case C		Case D	
	TCP	TVP	TCP	TVP	TCP	TVP	TCP	TVP
0.1/0.9	205 230.8	4 280.660	205 529.2	4 703.152	205 230.8	4 074.115	205 529.2	4 751.198
0.2/0.8	205 449.2	4 315.470	206 462.2	4 795.312	205 449.2	4 101.700	205 529.2	4 751.198
0.3/0.7	205 529.2	4 322.240	208 012.2	4 906.480	205 529.2	4 107.040	208 012.2	4 964.222
0.4/0.6	205 529.2	4 322.240	208 012.2	4 906.480	205 529.2	4 107.040	210 665.4	5 070.365
0.5/0.5	208 012.2	4 387.232	210 665.4	4 995.489	208 012.2	4 158.304	210 665.4	5 070.365
0.6/0.4	208 012.2	4 387.232	210 665.4	4 995.489	208 012.2	4 158.304	210 665.4	5 070.365
0.7/0.3	210 665.4	4 416.676	210 665.4	4 995.489	210 665.4	4 184.698	210 665.4	5 070.365
0.8/0.2	210 665.4	4 416.676	210 665.4	4 995.489	210 665.4	4 184.698	210 665.4	5 070.365
0.9/0.1	210 665.4	4 416.676	210 665.4	4 995.489	210 665.4	4 184.698	210 665.4	5 070.365

Table 21 Optimal TCP and TVP values with β_G/β_T = 0.4/0.6

ω_1/ω_2	Case A		Case B		Case C		Case D	
	TCP	TVP	TCP	TVP	TCP	TVP	TCP	TVP
0.1/0.9	205 230.8	4 350.212	205 529.2	4 474.735	205 230.8	4 149.426	205 529.2	4 524.612
0.2/0.8	205 449.2	4 377.495	206 462.2	4 579.375	205 449.2	4 171.669	205 529.2	4 524.612
0.3/0.7	205 529.2	4 383.435	208 012.2	4 664.431	205 529.2	4 176.199	208 012.2	4 713.060
0.4/0.6	205 529.2	4 383.435	208 012.2	4 664.431	205 529.2	4 176.199	208 012.2	4 713.060
0.5/0.5	206 462.2	4 411.947	210 665.4	4 738.221	205 529.2	4 176.199	210 665.4	4 795.543
0.6/0.4	208 012.2	4 440.459	210 665.4	4 738.221	208 012.2	4 219.687	210 665.4	4 795.543
0.7/0.3	208 012.2	4 440.459	210 665.4	4 738.221	208 012.2	4 219.687	210 665.4	4 795.543
0.8/0.2	210 665.4	4 464.100	210 665.4	4 738.221	210 665.4	4 240.025	210 665.4	4 795.543
0.9/0.1	210 665.4	4 464.100	210 665.4	4 738.221	210 665.4	4 240.025	210 665.4	4 795.543

Table 22 Optimal TCP and TVP values with β_G/β_T = 0.6/0.4

ω_1/ω_2	Case A		Case B		Case C		Case D	
	TCP	TVP	TCP	TVP	TCP	TVP	TCP	TVP
0.1/0.9	205 230.8	4 419.763	205 529.2	4 246.319	205 230.8	4 224.738	205 529.2	4 298.025
0.2/0.8	205 449.2	4 439.520	206 462.2	4 363.439	205 230.8	4 224.738	206 462.2	4 398.345
0.3/0.7	205 529.2	4 444.630	206 462.2	4 363.439	205 449.2	4 241.639	206 462.2	4 398.345
0.4/0.6	205 529.2	4 444.630	208 532.2	4 441.903	205 529.2	4 245.359	208 012.2	4 461.897
0.5/0.5	206 462.2	4 474.198	208 532.2	4 441.903	205 529.2	4 245.359	208 532.2	4 478.617
0.6/0.4	206 462.2	4 474.198	210 665.4	4 480.953	206 462.2	4 264.271	210 665.4	4 520.720
0.7/0.3	208 532.2	4 498.614	210 665.4	4 480.953	208 012.2	4 281.071	210 665.4	4 520.720
0.8/0.2	210 665.4	4 511.525	210 665.4	4 480.953	208 532.2	4 284.223	210 665.4	4 520.720
0.9/0.1	210 665.4	4 511.525	210 665.4	4 480.953	210 665.4	4 295.353	210 665.4	4 520.720

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Table 23 Optimal TCP and TVP values with β_G/β_T=0.8/0.2

ω_1/ω_2	Case A		Case B		Case C		Case D	
	TCP	TVP	TCP	TVP	TCP	TVP	TCP	TVP
0.1/0.9	205 230.8	4 489.315	205 538.2	4 020.128	205 230.8	4 300.049	205 449.2	4 056.929
0.2/0.8	205 230.8	4 489.315	206 462.2	4 147.502	205 230.8	4 300.049	206 462.2	4 186.639
0.3/0.7	205 529.2	4 505.825	206 462.2	4 147.502	205 449.2	4 311.608	206 462.2	4 186.639
0.4/0.6	205 538.2	4 506.209	206 982.2	4 169.102	205 529.2	4 314.518	206 982.2	4 205.839
0.5/0.5	206 462.2	4 536.449	208 532.2	4 201.934	206 462.2	4 335.254	206 982.2	4 205.839
0.6/0.4	206 462.2	4 536.449	208 532.2	4 201.934	206 462.2	4 335.254	208 532.2	4 229.935
0.7/0.3	206 982.2	4 541.553	210 665.4	4 223.685	206 462.2	4 335.254	208 532.2	4 229.935
0.8/0.2	208 532.2	4 552.017	210 665.4	4 223.685	206 982.2	4 338.710	210 665.4	4 245.898
0.9/0.1	210 665.4	4 558.949	210 665.4	4 223.685	208 532.2	4 345.910	210 665.4	4 245.898

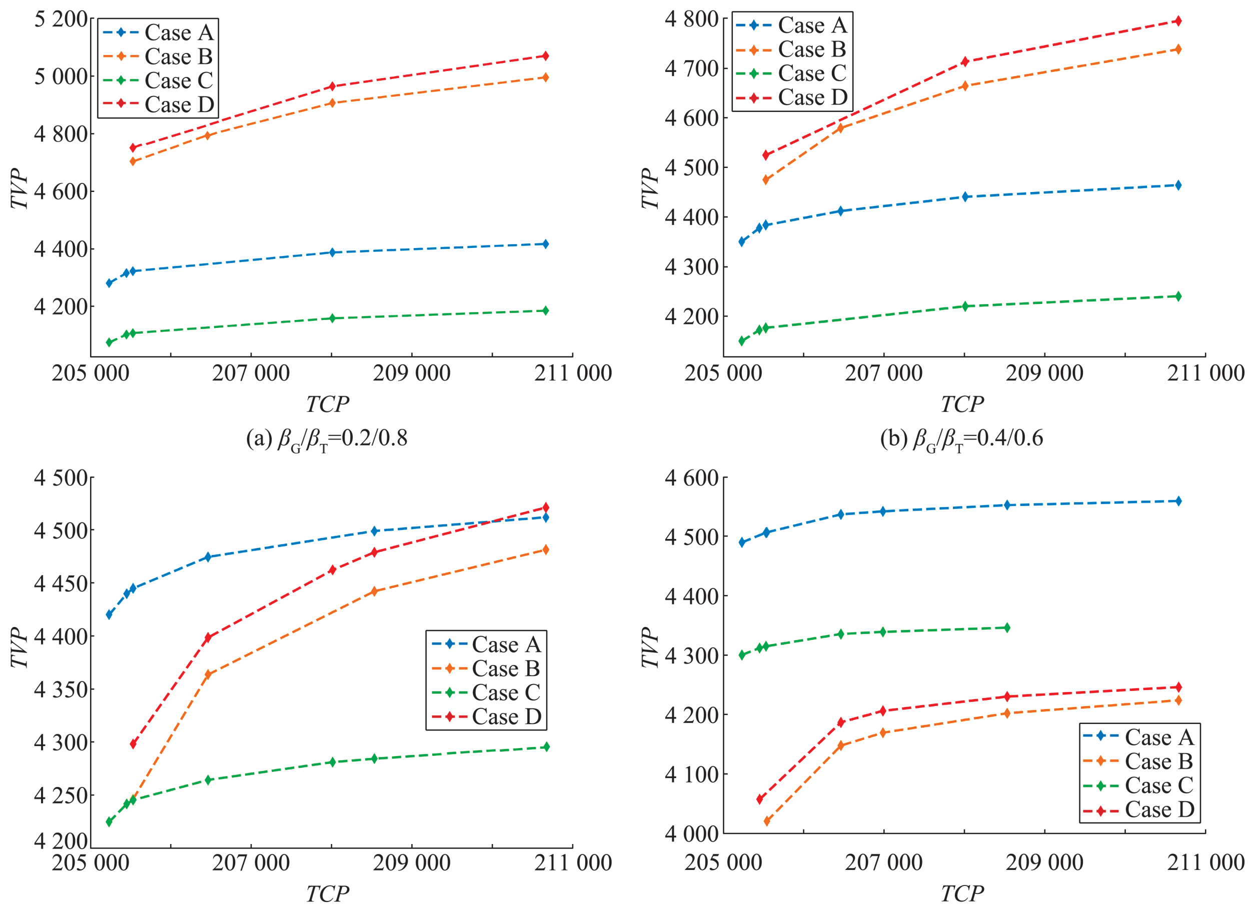

Fig. 6 Pareto set for Cases A-D under different β_G/β_T

4 Conclusions

In this paper, we present a dynamic framework for green supplier selection and order allocation, where quantity discounts, time-varying costs, and a number of suppliers are involved. First, we adopt fuzzy TOPSIS to identify the closeness coefficients for each vendor with regard to conventional and green criteria. Then, we introduce a group AHP that assigns weights to traditional and green standards considering the preference weights of the managers. At last, a numerical example is demonstrated to verify the validity of the suggested framework. In addition, we conduct alternative ranking analysis based on four types of TOPSIS methods and then investigate the effects of the conventional and green criteria weights, as well as Pareto set.

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