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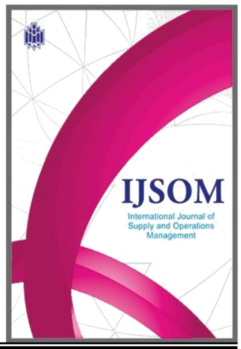

Supplier Selection Models for Complementary, Substitutable, and Conditional Products

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Abstract

The supplier selection process, as one of the components of the supply chain management (SCM), refers to evaluating and selecting suitable suppliers based on relevant criteria. This study presents two supplier selection models to supply complementary, substitutable, and conditional products. For this purpose, two multi-objective mixed-integer non-linear programming (MOMINLP) models are formulated to select the suppliers with the highest scores, the lowest total cost, and the highest quality. To identify the criteria weights and to score the suppliers, first, one of the effective multiple criteria decision-making (MCDM) methods, called the Best-Worst Method (BWM), is employed. Then, the weighted relative deviations from the ideal values of the criteria are minimized to solve the multi-objective models. Finally, two case studies are represented to show the practical application of the proposed methodology in the decision-making process.

Keywords: Supplier Selection; Supply Chain Management; BWM; Complementary Products; Substitutable Products; Conditional Products.

1. Introduction

The supplier selection problem has been recognized as a critical process for most business organizations, with a direct impact on the supply chain management (SCM) (Bohner and Minner, 2017). Identifying, screening, assessing, analyzing, and making contracts with suppliers are all parts of the process concerned, which require substantial finance and human resources (Chai and Ngai, 2020). Selecting the best suppliers can accordingly simplify other steps in the SCM (Davoudabadi et al., 2020) and even lead to decreased costs as well as improved flexibility and quality (Yazdani et al., 2017).

This paper integrates the Best-Worst Method (BWM) and the multi-objective mixed-integer non-linear programming (MOMINLP) models to select the suppliers. The main contribution of this study is considering the complementary, substitutable, and conditional products in the supplier selection process. As shown in Fig. 1, first, two MOMINLP models are presented for the complementary and substitutable products, as well as conditional products to choose the suppliers with the highest scores, the lowest total cost, and the highest product quality. Then, the criteria and the suppliers are evaluated using the BWM. Afterwards, the multi-objective problems are solved through minimizing the weighted relative deviations from the ideal values of the criteria. Finally, two case studies relative to a pharmaceutical company are utilized to show the practical application of the proposed methodology.

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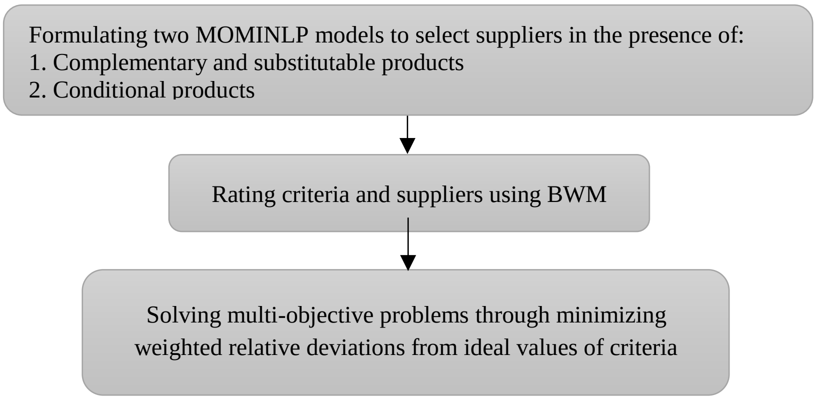

Figure 1. Methodology

2. Literature Review

The related literature includes several publications, applying different individual approaches to evaluate the best suppliers, including multi-attribute utility methods (MAUMs), such as the analytic hierarchical process (AHP) and the analytic network process (ANP); outranking methods, e.g., the preference ranking organization method for enrichment of evaluations (PROMETHEE), the QUALIFLEX approach, and the ELimination Et Choix Traduisant la REalité (ELECTRE); compromise methods, such as the technique for order of preference by similarity to ideal solution (TOPSIS) and the Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR); and mathematical programming techniques, e.g., the data envelopment analysis (DEA) and the goal programming (GP) (Chai and Ngai, 2020; Forghani et al., 2021). Gaballa (1974) was the first researcher who used linear programming (LP) in the supplier selection problem. As well, Dahel (2003) proposed an MOMILP model to select the suppliers, considering volume discount. Wadhwa and Ravindran (2007) similarly developed a multi-objective programming model with regard to price, lead-time, and number of rejects. Comparably, Kull and Talluri (2008), and Razmi and Keramati (2011) presented GP models to score the suppliers. In this sense, Ordoobadi (2010) applied the AHP to evaluate tangible and intangible factors, and ranked the suppliers by calculating the weighted Taguchi loss scores. Moreover, Guo and Li (2014) investigated a mathematical problem, considering stochastic demand and lead-time, to determine the appropriate suppliers and the optimal inventory policies in a multi-echelon system. A multi-objective programming model was further presented by Azadnia (2016) to balance costs under inflation in a sustainable supply chain. As well, Amorim et al. (2016) constructed a stochastic programming model, which could increase profits and reduce customer service risks under uncertainty. Fathollah Bayati and Sadjadi (2016) correspondingly presented cooperative and non-cooperative models, using the DEA to evaluate the performance of two-tier suppliers. Considering the inter-relationships between sustainability-related evaluation metrics, Giannakis et al. (2020) also introduced a novel model for supplier selection via the ANP.

Several studies have also employed integrated approaches to solve suppler selection problems. For instance, Lin et al. (2011) applied the ANP and the TOPSIS to rank the suppliers, and presented an LP model for order allocation. Shaw et al. (2012) also developed a method applying the fuzzy AHP and the fuzzy LP to evaluate the suppliers. Taking into account the interdependence among the criteria, Kuo and Lin (2012) applied the ANP combined with the DEA method for green supplier selection. An integrated model was further suggested by Lee et al. (2013) to find the answer to the lot-sizing problem, considering quantity discounts by genetic algorithms. In this regard, Pramanik et al. (2017) developed an approach to measure the importance of suppliers using the TOPSIS, the AHP, and the quality function deployment (QFD). Forghani et al. (2018) also proposed an MILP model to increase the supplier scores resulted from Z-TOPSIS method. As well, El-Hiri et al. (2019) proposed a generic model based on the ANN to select the suppliers in terms of risks. Memari et al. (2019) additionally applied the intuitionistic fuzzy TOPSIS and the MOMILP to deal with the sustainable supplier selection problem. In this respect, Ho (2019) presented weighted multi-choice GP and gave different weights to focus on some goals. She also proposed the MinMax multi-choice GP to eliminate the impact of some scales on each goal. Furthermore, Kilic and Yalcin (2020) proposed a green supplier selection model, using the intuitionistic fuzzy TOPSIS and a modified two-phase fuzzy GP model to find a solution, considering both green and classic scores of suppliers. Zare Mehrjerdi and Lotfi (2019) also used the MILP and a robust counterpart model in a closed-loop supply chain network. Reflecting on sustainable development in scheduling projects, Lotfi et al., (2020) presented a robust non-linear programming (NLP) and applied augmented ε-constraint method to solve it. Likewise, Fakhrzad and Lotfi (2018) applied the ε-constraint method and the non-dominated sorting genetic algorithm II (NSGA-II) approach in green backorder vendor managed inventory in two-echelon supply chain models.

This paper integrates the BWM and the MOMINLP models to select the suppliers in the presence of complementary, substitutable, and conditional products.

3. Problem Statement

In some industries, not all products can be directly purchased. Such products are derived from a combination of two (or more) products, which are functionally complementary to each other. These products must be thus purchased from suppliers and then combined by the company. This combination is not necessarily unique. A simple example is illustrated in Fig. 1 in which either "products A and B" or "products C and D" can be combined to obtain product S. In other words, "products A and B" and "products C and D" are substitutable, and depending on the constraints and the objective functions, it is determined which pair to buy. In fact, the functionality of the combination of products A and B is the same as that of the combination of products C and D, and therefore, they are substitutable.

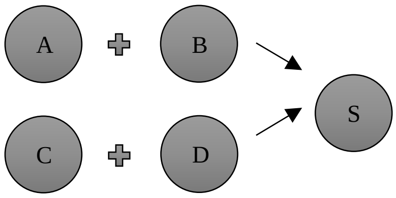

Figure 1. Complementary and substitutable products

In this research, conditional products were also examined. Buying one of these products would necessitate the purchase of the other one to obtain the full utility of the products. A simple example is presented in Fig. 2, in which it is assumed that products A and C are functionally similar and the company decides to purchase both of them in total for a known amount; for example, buying a total of 20 of these products can lead to purchasing 16 of A and 4 of C or 10 of A and 10 of C. On the other hand, products A and C are conditional, which means, if product A is acquired, product B must be also purchased, and product C must be obtained if product D is purchased.

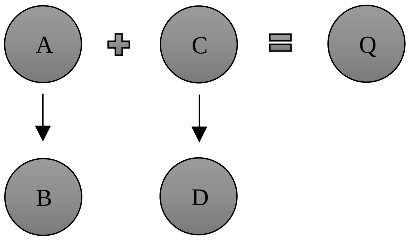

Figure 2. Conditional products

3.1. MOMINLP Models

To deal with such products, two MOMINLP models are presented. These models are developed to allocate the orders among suppliers. The first model is formulated in the presence of the complementary and substitutable products, and the second one deals with the conditional products.

Assumptions

1. A multi-item/multi-supplier environment for one single period is considered.
2. The number of suppliers and product amounts are known.
3. A limited budget has been allocated to buy all products.
4. Demand is considered constant.

Indices

i products
j suppliers
k the pair of complementary products
t products that cannot be purchased directly from suppliers

Parameters

SC_{ij} the score of supplier j relative to product i resulted from BWM
B_T budget
P_{ij} the price of product i bought from supplier j
F_{ij} the average number of imperfect items of product i bought from supplier j
D_i demand for product i

s_{ij}, S_{ij} minimum and maximum capacity of product i pertinent to supplier j, respectively
r_{ij}, R_{ij} minimum and maximum order for product i from supplier j, respectively
m, M minimum and maximum to which the number of selected suppliers is restricted, respectively
Q_t total demand for product t

Decision Variables
x_{ij} the amount of product i bought from supplier j
y_{ij} binary decision variable

$$y_{ij} = \begin{cases} 1, & \text{if product } i \text{ is bought from supplier } j \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

y_k binary decision variable , which is one if the pair of complementary products k is purchased and zero, otherwise
y_{a+t} binary decision variable, which is one if product $a + t$ is purchased and zero, otherwise
y_{c+t} binary variable, which is one if product $c + t$ is purchased and zero, otherwise

3.1.1. Complementary and Substitutable Products

In the presence of complementary and substitutable products, it is assumed that the index i is determined as follows:

$$\begin{aligned} & i = 1, \dots, a, \\ & \overbrace{a+1, \dots, a+t, \dots,\ a+T}^{T}, \overbrace{b+1, \dots, b+t, \dots, b+T}^{T}, \\ & \overbrace{c+1, \dots, c+t, \dots c+T}^{T}, \overbrace{d+1, \dots, d+t, \dots, d+T}^{T}. \end{aligned} \tag{2}$$

It is also supposed that the amount of the required products is x_{ij} $(i = 1, \cdots, a,\ j = 1, \cdots, n)$ and S_t $(t = 1, \cdots, T)$. Product i $(i = 1, \dots, a)$ can be also provided directly from the suppliers. For product t $(t = 1, \dots, T)$, either products $a + t$ and $b + t$ or products $c + t$ and $d + t$ can be combined.

$$\sum_{j=1}^{n} x_{a+t\ j} + \sum_{j=1}^{n} x_{b+t\ j} \le S_t, \qquad t = 1, \dots, T, \tag{3}$$

or

$$\sum_{j=1}^{n} x_{c+t\ j} + \sum_{j=1}^{n} x_{d+t\ j} \le S_t, \qquad t = 1, \dots, T. \tag{4}$$

In other words, the functionality of $a + t$ and $b + t$ is the same as that of $c + t$ and $d + t$, and therefore, they are substitutable. As a result, by solving the model, it is determined which of the two pairs of complementary products to purchase:

$$\begin{aligned} & x_{a+1\ j}\ \&\ x_{b+1\ j} \ \text{ or }\ x_{c+1\ j}\ \&\ x_{d+1\ j} \\ & x_{a+2\ j}\ \&\ x_{b+2\ j} \ \text{ or }\ x_{c+2\ j}\ \&\ x_{d+2\ j} \\ & \qquad \vdots \\ & x_{c+T\ j}\ \&\ x_{d+T\ j} \ \text{ or }\ x_{a+T\ j}\ \&\ x_{b+T\ j} \end{aligned} \tag{5}$$

The MOMINLP model for the complementary and substitutable products can be formulated as follows:

$$\text{Max} \quad Z_1 = \sum_{i=1}^{d+T} \sum_{j=1}^{n} SC_{ij} x_{ij} \tag{6}$$

$$\text{Min} \quad Z_2 = \sum_{i=1}^{d+T} \sum_{j=1}^{n} P_{ij} x_{ij} \tag{7}$$

$$\text{Min} \quad Z_3 = \sum_{i=1}^{d+T} \sum_{j=1}^{n} F_{ij} x_{ij} \tag{8}$$

$$\text{s.t.} \quad \sum_{i=1}^{d+T} \sum_{j=1}^{n} P_{ij} x_{ij} \le B_T, \tag{9}$$

$$D_i \le \sum_{j=1}^{n} (1 - d_{ij})\, x_{ij}, \qquad \boldsymbol{i = 1, \dots, a}, \tag{10}$$

$$D_i y_k \le \sum_{j=1}^{n} (1 - d_{ij})\, x_{ij} \le \left(\sum_{j=1}^{n} x_{ij} \right) y_k, \qquad \boldsymbol{i, k = a + 1, \dots, a + T,} \tag{11}$$

$$D_i y_k \le \sum_{j=1}^{n} (1 - d_{ij})\, x_{ij} \le \left(\sum_{j=1}^{n} x_{ij} \right) y_k, \qquad i = b + 1, \dots, b + T,\ k = a + 1, \dots, a + T, \tag{12}$$

$$D_i y_k \le \sum_{j=1}^{n} (1 - d_{ij})\, x_{ij} \le \left(\sum_{j=1}^{n} x_{ij} \right) y_k, \qquad i, k = c + 1, \dots, c + T, \tag{13}$$

$$D_i y_k \le \sum_{j=1}^{n} (1 - d_{ij})\, x_{ij} \le \left(\sum_{j=1}^{n} x_{ij} \right) y_k, \qquad i = d + 1, \dots, d + T,\ k = c + 1, \dots, c + T, \tag{14}$$

$$y_k + y_{k+2T} = 1, \qquad \boldsymbol{k = a + 1, \dots, a + T,} \tag{15}$$

$$s_{ij} y_{ij} \le x_{ij} \le S_{ij} y_{ij}, \qquad \boldsymbol{i = 1, \dots, d + T, j = 1, \dots, n} \tag{16}$$

$$r_{ij} y_{ij} \le x_{ij} \le R_{ij} y_{ij}, \qquad \boldsymbol{i = 1, \dots, d + T, j = 1, \dots, n} \tag{17}$$

$$m \le \sum_{i=1}^{d+T} \sum_{j=1}^{n} y_{ij} \le M. \tag{18}$$

$$x_{ij}, \ge 0, y_{ij}, y_k \in \{0,1\}. \qquad \boldsymbol{\forall i, j, k.} \tag{19}$$

The objective function (6) determines the suppliers with the highest scores. The objective functions (7) and (8) are to reduce the total cost and the average of the defective items, respectively. Constraint (9) guarantees that the total costs do not go over the budget limit. Constraint sets (10-15) are associated with demands. In constraint (15), y_k and y_{k+2T} are the binary decision variables; therefore, there are two possibilities:

1. y_k=1 and y_{k+2T}=0 ($k = a + 1, \dots, a + t, \dots , a + T$): In this case, both constraints (13) and (14) would be omitted and constraints (11) and (12) would lead to purchasing products $a + t$ and $b + t$.

2. y_k=0 and y_{k+2T}=1 ($k = a + 1, \dots, a + t, \dots , a + T$): In this case, both constraints (11) and (12) would be omitted and constraints (13) and (14) would lead to purchasing products $c + t$ and $d + t$.

Therefore, constraint (15) ensures that only one pair of substitute products will be purchased.

Constraint sets (16) and (17) also guarantee that the ordered amount of products lies within the capacity and the demand, respectively. Finally, the number of suppliers is limited by constraint (18).

3.1.2. Conditional Products

In the presence of conditional products, it is assumed that the amount of products required by the company is x_{ij} ($i = 1, \cdots, a,\ j = 1, \cdots, n$) and Q_t ($t = 1, \cdots, T$). Product i ($i\ =\ 1, \dots, a$) can be also directly provided from the suppliers. Products $a + t$ and $c + t$ are functionally similar. They are purchased in total at least for a known amount, Q_t. If product $a + t$ is bought, product $b + t$ must be also purchased, and if product $c + t$ is purchased, the product $d + t$ must be obtained:

$$\sum_{j=1}^{n} x_{a+t\ j} + \sum_{j=1}^{n} x_{c+t\ j} \le Q_t, \qquad t = 1, \dots, T, \tag{20}$$

$$\sum_{j=1}^{n} x_{a+t\ j} \le \sum_{j=1}^{n} x_{b+t\ j}, \qquad t = 1, \dots, T, \tag{21}$$

$$\sum_{j=1}^{n} x_{c+t\ j} \le \sum_{j=1}^{n} x_{d+t\ j}, \qquad t = 1, \dots, T. \tag{22}$$

The MOMINLP model for conditional products can be formulated as follows:

$$Q_t \le y_{a+t} \sum_{j=1}^{n} (1 - d_{a+t\,j})\, x_{a+t\,j} + y_{c+t} \sum_{j=1}^{n} (1 - d_{c+t\,j})\, x_{c+t\,j}, \qquad \boldsymbol{t = 1, \dots, T}, \tag{23}$$

$$\sum_{j=1}^{n} (1 - d_{a+t\,j})\, x_{a+t\,j} \le \sum_{j=1}^{n} (1 - d_{b+t\,j})\, x_{b+t\,j} \le y_{a+t} \sum_{j=1}^{n} x_{b+t\,j}, \qquad \boldsymbol{t = 1, \dots, T}, \tag{24}$$

$$\sum_{j=1}^{n} (1 - d_{c+t\,j})\, x_{c+t\,j} \le \sum_{j=1}^{n} (1 - d_{d+t\,j})\, x_{d+t\,j} \le y_{c+t} \sum_{j=1}^{n} x_{d+t\,j}, \qquad \boldsymbol{t = 1, \dots, T}, \tag{25}$$

$$y_{a+t}, y_{c+t} \in \{0,1\}. \qquad \forall \boldsymbol{i, j, t}. \tag{26}$$

Constraint (23) guarantees that the similar products $a + t$ and $c + t$ will be purchased at least Q_t. Constraint (24) also ensures that product $b + t$ will be purchased if product $a + t$ is acquired. Moreover, constraint (25) guarantees that product $d +$ t will be purchased if product $c + t$ is bought. The objective functions (6-8) and the rest of the constraints (9), (10), (16-19) are the same as those in the first model.

In the next section, the BWM, used to calculate the score of supplier *j* relative to product *i* as for the multiplier in the first objective function (SC_{ij}) in both models, will be reviewed.

3.2. BWM

Over the past years, considerable efforts have been made to introduce multiple criteria decision-making (MCDM) methods. In this respect, the AHP is a pioneer method proposed by Saaty (1980). Accordingly, so many comparisons will be performed if there are a large number of criteria, and consequently, inconsistency will appear in the results. Rezaei (2015) also proposed the BWM, which utilizes only two criteria (viz. the best [*B*] and the worst [*W*] criteria) for pairwise comparisons. Compared with the AHP, the BWM requires fewer comparisons and results in consistent weights.

To identify the criteria weights, the BWM (Rezaei, 2016) is practiced. The implementation steps of this technique are described below:

Step 1. Identify the decision criteria $\{c_1, c_2, \dots, c_n\}$.

Step 2. Identify the *B* and the *W* criteria.

Step 3. Perform pairwise comparisons between *B* and the other criteria, via a number from 1 to 9. $A_B = (a_{B1}, a_{B2}, \dots, a_{Bl}, \dots, a_{Bn})$ would be the Best-to-Others (*BO*) vector, where a_{Bl} denotes the superiority of *B* over criterion *l*, and a_{BB} is equal to 1.

Step 4. Perform pairwise comparisons between all the criteria and *W*, via a number from 1 to 9. $A_W = (a_{1W}, a_{2W}, \dots, a_{lW}, \dots a_{nW})^T$ would be the Others-to-Worst (*OW*) vector, where a_{lW} denotes the superiority of the criterion *l* over *W*, and a_{WW} is equal to 1.

Step 5. Find the optimal criteria weights $(W_1^*, W_2^*, \dots, W_n^*)$ and ξ^{L*} by solving the following problem:

$$\begin{aligned} \text{Min} \quad & \xi^L \\ \text{s.t.} \quad & |W_b - a_{Bl} \cdot W_l| \le \xi^L, && \forall l \\ & |W_l - a_{lW} \cdot W_W| \le \xi^L, && \forall l \\ & \textstyle\sum_{l=1}^{n} W_l = 1, && \forall l \\ & W_l \ge 0 && \forall l \end{aligned} \tag{27}$$

For this model, ξ^{L*} can be directly considered as the consistency ratio of the comparisons. The closer the ξ^{L*} to zero, the higher the degree of consistency.

In the next section, a scalarization technique, employed to solve multi-objective models, will be reviewed.

3.3. Solution Method

Through the minimization of the weighted relative deviations from the ideal values of the criteria (Marler and Arora, 2004), a multi-objective function problem can be converted into a problem with a single-objective function, as defined in Eq. (28):

$$\text{Min } Z = \sum_{k=1}^{K} w_k \cdot Z'_k = \sum_{k=1}^{K} w_k \cdot \frac{Z_k - Z_k^*}{Z_k^*}, \tag{28}$$

where, Z'_k refers to the normalized objective function and Z_k^* stands for the optimal value of k^{th} objective function when solved separately. In this method, the decision-maker (DM) can control the importance weights (w_k) attributed to the normalized Z_k, where $\sum_{k=1}^{K} w_k = 1$.

The reason why this method is used is its simplicity and efficiency, as for the number of the Pareto solutions (Hamdan and Cheaitou, 2017).

4. Numerical Example

In this section, two case studies relative to a pharmaceutical company, as for each model, are provided to show the practical application of the proposed models. Table 1 lists seven evaluation criteria, identified according to the literature review and expert opinions (Forghani et al., 2018):

Table 1. Supplier selection criteria

Criteria		Sub-criteria
C_1	Cost	Product price; Payment terms; Delivery cost
C_2	Quality	Product quality; Defective items; Packaging and labeling; the International Organization for Standardization (ISO) 9001; Research and development
C_3	Services	Customer relationship management; After-sales services/warranty
C_4	Delivery	Geographical location; On-time delivery
C_5	Supplier profile	Financial status; Management and organization; Technical ability; Facilities; Capacity; Record documentation; Certificate of good manufacturing practices (GMP); ISO 14001; Occupational Health and Safety Assessment Series (OHSAS) 18001
C_6	Risk	Sanction; Currency fluctuation; Inflation rate; Money transfer; War and terrorism; Changes in tariff policies
C_7	Personnel capabilities	Labor overall skills; Labor experience

4.1. MOMINLP Model for Complementary and Substitutable Products

4.1.1. Determining the Criteria Weights

In the first case, there are four suppliers, five products, and an expert group of four DMs, including a production manager, a production expert, a quality control manager, and a laboratory supervisor. The BWM is applied to determine the weights of each criterion relative to product 1. Each DM identifies *B*, *W*, *BO*, and *OW*. Tables 2 and 3 illustrate the results:

Table 2. BO pairwise comparison vectors for four DMs

DM	Criteria / B	C_1	C_2	C_3	C_4	C_5	C_6	C_7
DM$_1$	C_2	2	1	6	7	3	4	9
DM$_2$	C_1	1	2	5	7	3	4	9
DM$_3$	C_2	2	1	9	8	3	3	6
DM$_4$	C_2	2	1	5	9	6	3	8

Table 3. OW pairwise comparison vectors for four DMs

DM	DM$_1$	DM$_2$	DM$_3$	DM$_4$
W / Criteria	C_7	C_7	C_3	C_7
C_1	8	9	8	8
C_2	9	8	9	9
C_3	4	5	1	5
C_4	3	3	2	1
C_5	7	7	7	4
C_6	6	6	7	7
C_7	1	1	4	2

As outlined in Table 4, the weights and the consistency ratios are determined using the linear model (27). Then, the averages are computed for each criterion.

Table 4. Criteria weights and consistency ratios

DM	W_1^*	W_2^*	W_3^*	W_4^*	W_5^*	W_6^*	W_7^*	ξ^{L*}
DM1	0.22	0.36	0.07	0.06	0.146	0.11	0.03	0.08
DM2	0.35	0.22	0.09	0.06	0.14	0.11	0.03	0.08
DM3	0.21	0.35	0.03	0.05	0.14	0.14	0.07	0.07
DM4	0.23	0.37	0.09	0.03	0.08	0.15	0.06	0.08
Average	0.25	0.32	0.07	0.05	0.13	0.13	0.05	0.08

Accordingly, the ranking results of the seven criteria are derived as quality ≻ cost ≻ risk ≻ supplier profile ≻ services ≻ delivery ≻ personnel capabilities. Since ξ^{L*} has a value close to zero, it is concluded that the computation is highly stable.

4.1.2. Ranking the Suppliers

In order to calculate the scores of the suppliers, each DM is asked to identify the performance of each supplier according to different criteria. Table 5 shows the average results for each supplier.

Table 5. Supplier performance according to criteria

Supplier	C_1	C_2	C_3	C_4	C_5	C_6	C_7
S1	8	4.5	4.5	7	4.75	5.5	4.25
S2	6.5	6.25	7.5	5.75	4.5	6.25	6.75
S3	6.75	4.25	6	6.5	4.75	7	6.75
S4	6.25	5.75	3.75	4.25	4	3.75	5

Then, the weighted average is calculated to obtain the scores of the suppliers. The final scores of the suppliers and the rankings are as follows:

Table 6. Supplier scores

Supplier	Score	Rank
S1	5.66	2
S2	6.18	1
S3	5.65	3
S4	5.15	4

As shown in Table 6, the ranking results of the four suppliers relative to product 1 are derived as $S_2 \succ S_1 \succ S_3 \succ S_4$.

Similar to the scores of product 1, the scores relative to products 2, 3, 4, and 5 are also obtained as follows:

$$SC_{ij} = \begin{bmatrix} 5.66 & 6.18 & 5.65 & 5.15 \\ 5.54 & 6.23 & 5.92 & 5.12 \\ 5.84 & 6.34 & 5.55 & - \\ 5.69 & - & 6.54 & 5.03 \\ 5.10 & - & 5.30 & 5.47 \end{bmatrix},$$

It should be noted that since there are only seven criteria and four suppliers (namely, alternatives) in this numerical example, it is no trouble to apply the AHP for a problem of this size. Generally, for the problems with a large number of criteria, it is much better to apply the BWM.

Taking these scores and other parameters into account, the non-linear model will be solved in the next section.

4.1.3. Solving the Model

Product 1 is a typical product that can be purchased from all suppliers. Products 2 and 3 are also complementary to each other, and can be substituted by products 4 and 5, which are complementary to each other, too. Therefore, the company has two alternatives: (1) purchasing products 1, 2, and 3 or (2) purchasing products 1, 4, and 5. According to the following parameters, the model will be solved using the method reviewed in section 3.3 through the General Algebraic Modeling System (GAMS) software:

$$P_{ij} = \begin{bmatrix} 2 & 4 & 3 & 4 \\ 1 & 3 & 2 & 3 \\ 2 & 2 & 3 & - \\ 3 & - & 4 & 2 \\ 5 & - & 4 & 3 \end{bmatrix}, F_{ij} = \begin{bmatrix} 0.11 & 0.02 & 0.11 & 0.02 \\ 0.04 & 0.02 & 0.07 & 0.08 \\ 0.10 & 0.02 & 0.06 & - \\ 0.02 & - & 0.01 & 0.06 \\ 0.11 & - & 0.8 & 0.09 \end{bmatrix}, D_i = \begin{bmatrix} 100 \\ 40 \\ 50 \\ 35 \\ 45 \end{bmatrix},$$

$$S_{ij} = \begin{bmatrix} 70 & 80 & 100 & 50 \\ 100 & 60 & 30 & 40 \\ 60 & 40 & 100 & 70 \\ 40 & 0 & 60 & 200 \\ 100 & 0 & 100 & 150 \end{bmatrix}, R_{ij} = \begin{bmatrix} 80 & 20 & 80 & 60 \\ 40 & 40 & 40 & 25 \\ 40 & 50 & 50 & 0 \\ 40 & 35 & 45 & 35 \\ 55 & 55 & 55 & 55 \end{bmatrix}, B_T = 600, s_{ij}, r_{ij} = 0, m = 0, M = 4.$$

As observed in Table 7, four scenarios are set to investigate the possible effect of different importance weights on the results.

Table 7. First model optimal solutions for scenarios

Scenario	x^*_{ij}	Z^*
Balanced $w_1 = 0.33$ $w_2 = 0.33$ $w_3 = 0.33$	$\begin{bmatrix} 35.28 & 20 & 0 & 50 \\ 40 & 1.63 & 0 & 0 \\ 0 & 40 & 11.49 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	0.220
Supplier-oriented $w_1 = 0.8$ $w_2 = 0.1$ $w_3 = 0.1$	$\begin{bmatrix} 70 & 20 & 0 & 18.47 \\ 40 & 34.043 & 30 & 0 \\ 12 & 40 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	0.199
Cost-oriented $w_1 = 0.1$ $w_2 = 0.8$ $w_3 = 0.1$	$\begin{bmatrix} 70 & 0 & 42.36 & 0 \\ 40 & 0 & 1.72 & 0 \\ 12 & 40 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	0.140
Quality-oriented $w_1 = 0.1$ $w_2 = 0.1$ $w_3 = 0.8$	$\begin{bmatrix} 35.28 & 20 & 0 & 50 \\ 0.83 & 40 & 0 & 0 \\ 0 & 40 & 11.49 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	0.072

In the first scenario, equal weights are assigned to each objective function. Within the second scenario, the first objective function, which selects the suppliers with the highest scores, has the highest weight. The maximum weight is also given to the second objective function in the third scenario, which minimizes the costs. In the fourth scenario, the third objective function, aimed to improve the quality, has the highest weight.

According to these results, the decision is not to buy products 4 and 5 in all scenarios; instead, products 2 and 3 will be purchased. Besides, the quality-oriented scenario yields a better response.

Fig. 4 illustrates the normalized optimal solution for each single-objective function and the final optimal solution. The best solution to each objective function is derived when only one objective function is optimized, without considering the other objectives. The figure indicates that all the objective functions have more balanced values without significant loss on any objective when the DMs determine the equal importance for each objective. Besides, the aggregated multi-objective function of the quality-oriented scenario results in the lowest value of all the scenarios. Therefore, the company should lay focus on quality in supply chain strategies since it may have more potential advantages compared with other criteria.

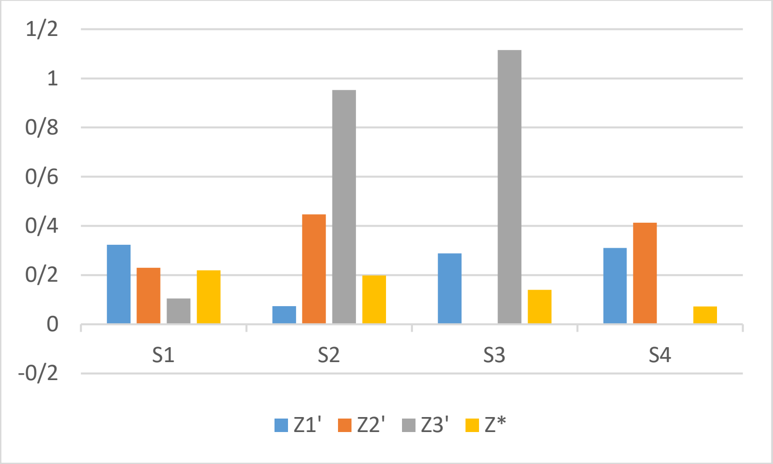

Figure 4. Normalized objective function values for decision scenarios

4.2. MOMINLP Model for Conditional Products

In the second case, there are four suppliers, an expert group of four DMs, four products, and seven evaluation criteria as listed in Table 1. It is assumed that products 1 and 3 are functionally similar and will be purchased at least for a known amount (Q_1=70). If product 1 is purchased, product 2 must be acquired, and if product 3 is purchased, product 4 must be bought. The scores relative to the products (SC_{ij}) are determined using the BWM. According to the following parameters, the model will be solved using the method reviewed in section 3.3 through the GAMS software:

$$SC_{ij} = \begin{bmatrix} 5.84 & 5.31 & 5.95 & 6.13 \\ 5.40 & 5.04 & 5.81 & 6.26 \\ 6.28 & 5.33 & 6.02 & 6.21 \\ 5.53 & 5.18 & 5.76 & 6.52 \end{bmatrix}, P_{ij} = \begin{bmatrix} 1 & 1 & 3 & 3 \\ 4 & 2 & 4 & 4 \\ 3 & 3 & 3 & 3 \\ 3 & 2 & 3 & 4 \end{bmatrix}, F_{ij} = \begin{bmatrix} 0.04 & 0.12 & 0.03 & 0.02 \\ 0.06 & 0.08 & 0.04 & 0.01 \\ 0.04 & 0.07 & 0.03 & 0.03 \\ 0.07 & 0.10 & 0.05 & 0.02 \end{bmatrix}$$

$$S_{ij} = \begin{bmatrix} 90 & 30 & 40 & 50 \\ 50 & 70 & 30 & 60 \\ 30 & 50 & 50 & 90 \\ 80 & 20 & 70 & 50 \end{bmatrix}, R_{ij} = \begin{bmatrix} 55 & 50 & 30 & 50 \\ 60 & 80 & 40 & 50 \\ 40 & 40 & 50 & 60 \\ 30 & 40 & 40 & 50 \end{bmatrix}, B_T = 400, s_{ij}, r_{ij} = 0, m = 0, M = 4.$$

The results are given below:

Table 8. Second model optimal solutions for scenarios

Scenario	x^*_{ij}	Z^*
Balanced	$\begin{bmatrix} 55 & 0 & 0 & 17.551 \\ 0 & 26.486 & 0 & 46.094 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	0.214
Supplier-oriented	$\begin{bmatrix} 55 & 0 & 0 & 28.287 \\ 0 & 70 & 0 & 16.284 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	0.203
Cost-oriented	$\begin{bmatrix} 39.583 & 30 & 0 & 0 \\ 0 & 70 & 0 & 30 \\ 0 & 0 & 0 & 5.773 \\ 0 & 6.222 & 0 & 0 \end{bmatrix}$	0.015
Quality-oriented	$\begin{bmatrix} 55 & 0 & 0 & 7.551 \\ 0 & 26.486 & 0 & 46.094 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	0.064

As presented in Table 8, product 2, and consequently, product 3 are acquired in the first, second, and forth scenarios, while product 4 and thus, product 5 are not purchased. The optimal values of the first and forth scenarios are equal, but the objective function values are not the same. In the vein of the previous model, a better solution is obtained when the maximum weight was given to the second objective function (i.e., minimizing the cost). Fig. 5 shows that all the objective functions have more balanced values in the supplier-oriented scenario.

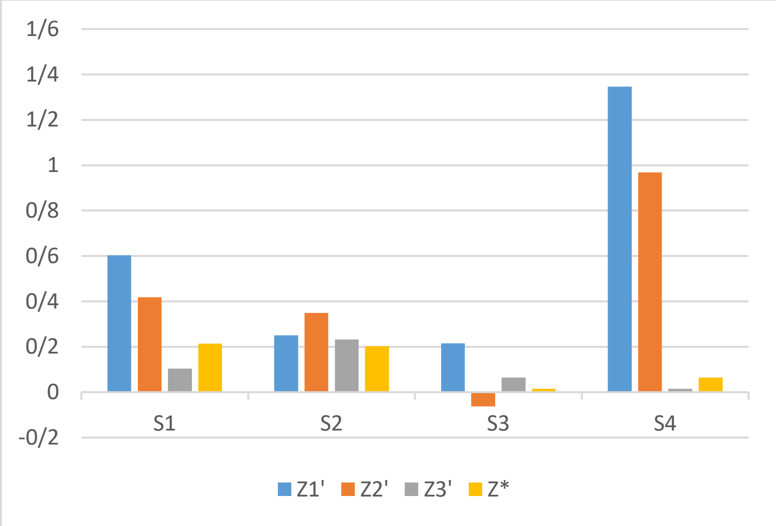

Figure 5. Normalized objective function values for decision scenarios

5. Conclusion

In this paper, two supplier selection models are developed for complementary, substitutable, and conditional products. In order to find the weight of the criteria and the score of the suppliers, the BWM is implemented. One of the major features of this technique is making fewer pairwise comparisons compared with other methods like the AHP, and deriving results that are more accurate, since it can reduce the inconsistency of pairwise comparisons. Then, by minimizing the weighted relative deviations from the ideal values of the criteria, the multi-objective mathematical models are solved. This method is not only simple but also effective. In this study, it has been assumed that the complementary products are derived from the combination of only two products, and there is only one substitutable pair for them. The model can be easily changed if there are more than two products to be combined, or there is more than one pair of substitutable products for them.

To confirm the practical application of the proposed models, a pharmaceutical company is considered. The results show that quality, cost, risk, supplier profile, services, delivery, and overall personnel capabilities are the most to the least important criteria. As the consistency indicator is close to zero, the computation is highly stable. Then, the models are solved based on different scenarios. The computational results show the validity of the solution method. In order to improve the supplier selection process, it is recommended to evaluate suppliers according to specific criteria and to conduct external audits periodically to enhance quality. The suggestions that can be further studied in this paper are listed below:

- Applying other MCDM methods like the VIKOR (Opricovic, 1998), the ANP (Saaty, 1996), and the TOPSIS (Hwang and Yoon, 1981)
- Considering price fluctuations
- Presenting new models based on a combination of structural equation modeling (SEM) and the BWM
- Adding uncertainty as a robust optimization to the suggested models
- Solving models using metaheuristic algorithms

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