

Research Article

An Integrated Model of Material Supplier Selection and Order Allocation Using Fuzzy Extended AHP and Multiobjective Programming

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This paper presents a supplier selection and order allocation (SSOA) model to solve the problem of a multiperiod supplier selection and then order allocation in the environment of short product life cycle and frequent material purchasing, for example, fast fashion environment in apparel industry. At the first stage, with consideration of multiple decision criteria and the fuzziness of the data involved in deciding the preferences of multiple decision variables in supplier selection, the fuzzy extent analytic hierarchy process (FEAHP) is adopted. In the second stage, supplier ranks are inputted into an order allocation model that aims at minimizing the risk of material purchasing and minimizing the total material purchasing costs using a dynamic programming approach, subject to constraints on deterministic customer demand and deterministic supplier capacity. Numerical examples are presented, and computational results are reported.

1. Introduction

Most manufacturers nowadays face cutthroat competition in the ever-changing market, which leads to establishment of network organizations. Supply chain management offers an integrated decision-making framework to administer such organizations. One of the key functions of supply chain management is the purchasing strategy. For a general producer, purchased items (e.g., raw materials) can account for 60% of total sales; purchasing shares normally account for 50% to 90% of total turnover in an industrial company [1]. Therefore, it is important to manage the process of supplier selection and the strategy of order allocation in order to construct a competitive and effective purchasing function.

Suitable suppliers can give a company a competitive edge and are instrumental to cost reduction and improvement in product quality. Various techniques have been presented to effectively evaluate and select suppliers. For order allocation problem, material purchasing managers firstly determine the optimal materials quantities purchased from each supplier during the purchasing period. An integrated mathematical

programming model has then been established to solve supplier selection and order allocation problems based on various assumptions adapting to real-world production.

1.1. Supplier Selection. To deal with supplier selection, many methodologies have been proposed, including categorical methods, case-based reasoning systems [2], statistical models [1], total cost of ownership models [3], mathematical programming, techniques for order preference by similarity to an ideal solution (TOPSISs) [4], and analytic hierarchy processes (AHP) [5]. Among these methods, the analytic hierarchy process (AHPs), first proposed by Saaty (1977), is a popular multiple criteria decision-making technique [6] combining qualitative with quantitative criteria. It is used to rank potential suppliers in a hierarchy system [7, 8]. However, the AHP frequently fails to adequately accommodate the inherent uncertainty and imprecision associated with mapping decision-makers' perceptions on extracted numbers. It is difficult to respond to preferences of decision-makers by assigning precise numerical values. As a result, the fuzzy

analytic hierarchy process (FAHP) is proposed [9, 10] which incorporates both the fuzzy nets theory and the AHP. To prioritize decision variables, Chan and Kumar [11] proposed the fuzzy extent analytic hierarchy process (FEAHP) which is used in different types of problem [12, 13]. In addition, order allocation is another important topic, especially in a multiple-supplier environment.

1.2. Order Allocation. For material purchasing process, after choosing suitable suppliers, order allocation is the next important stage to determine the optimal materials quantities purchased from each supplier, especially in a multiple-supplier environment. Various techniques have been developed to solve the optimal order allocation problem, including linear programming [14], nonlinear programming [15, 16], mixed-integer programming [17], and artificial intelligence technique [18–23]. These methods mainly focused on single objective optimization, that is, minimize cost. However, in a real-world supply chain environment, the decision-maker must consider uncertain factors along the supply chain. To reduce the risk, many scholars [24–26] proposed multiobjective optimization models to identify appealing tradeoffs between two or more conflicting objectives involved in the order allocation process. Furthermore, to deal with uncertainty, Xu and Nozick [27] proposed a two-stage mixed-integer stochastic programming model, which quantified the tradeoff between the risk and cost on the basis of ordering, thus determining optimal supplier sourcing decisions for varying levels of risk tolerance. To solve the multiperiod order allocation problem, dynamic programming has been utilized. Wagner and Whitin [28] employed a dynamic programming solution algorithm to solve a dynamic lot-sizing problem with the objective of minimizing the total cost, under time-varying demands for a single item, inventory holding charges, and setup costs. Basnet and Leung [29] extended the model, which has been proposed by Wagner and Whitin, to a multi-item order allocation problem, with multiple suppliers during a multiperiod planning horizon. Alidaee and Kochenberger [30] solved the single-sink, fixed charge transportation problem by using a dynamic programming method which is able to determine optimal order quantities from a set of potential suppliers to achieve the minimization of cost based on the total materials demands. Li et al. [31] compared periodically purchasing from the spot market with signing a long-term contract with a single supplier with consideration of fluctuant stochastic demand and price. Sawik [32] investigated the problem of multiperiod supplier selection and order allocation in make-to-order environment and proposed a mixed-integer programming approach to incorporate risk that uses conditional value-at-risk via scenario analysis, which is capable of optimizing the dynamic supply portfolio by calculating value-at-risk of cost per part and minimizing expected worst-case cost per part simultaneously.

Based on the aforementioned discussion, few studies [33, 34] have investigated material purchasing problems by integrating supplier evaluation and order allocation together. Specifically, research on material purchasing problems with consideration of the features of the fast fashion environment such as imprecise supplier evaluation measure and

multiperiod and multiobjective order allocation, has not been reported so far.

The main purpose of this paper is to develop a supplier selection and order allocation (SSOA) model, which is an effective multicriteria decision-making model, to handle material purchasing. Various features in fast fashion environment will be considered, including imprecise supplier evaluation measure, multiple order allocation objectives, varying purchasing prices, supplier capacities, and customer demands in different periods. The SSOA model will combine FEAHP with multiobjective dynamic linear programming technique to generate effective material purchasing solutions.

The rest of this paper is organized as follows. Section 2 presents the mathematical model of optimal order allocation based on supplier rankings. In Section 3, a supply selection (ranking) and order allocation model is developed. In Section 4, experimental results to validate the performance of the proposed model are presented. Conclusions are drawn and future research is suggested in Section 5.

2. Problem Description

To meet customers' demands and make a healthy profit, a manufacturer must make an effective sourcing plan based on customers' orders. In the textile industry, manufacturers always need to source common materials (e.g., white fabric) from suppliers over a planning horizon of different periods in order to encourage competition among suppliers and ensure access to a wide variety of goods or services. Therefore, selection of suitable suppliers and an optimal order allocation plan become crucial. This study proposes a model to handle optimal order allocation based on supplier ranking.

The assumptions of this study are as follows.

- (1) Each supplier can provide materials for manufacturers, and suppliers have different production capacities.
- (2) Manufacturers can get information on each supplier in terms of production capacity and price at the beginning of each planning horizon.
- (3) There is no inventory of materials, and manufacturers need to purchase all materials for production.

Let $I = \{1, \dots, N\}$ represent the set of N suppliers, $J = \{1, \dots, M\}$ the set of M customer orders, and $T = \{1, \dots, H\}$ the set of T planning periods. x_{it} denotes the order quantity from supplier i . c_{it} denotes the capacity of supplier i ($i \in I$) in period t . p_{it} denotes the unit price of the material purchased from supplier i ($i \in I$) in period $t \in T$. D_t represents manufacturers' demands for materials based on customers' orders, known ahead of material purchasing. r_i represents the relative risk index of supplier i , which indicates that a higher value of r_i can generate a higher real purchasing risk. Supplier ranking and order allocation investigated in this research can be formulated as follows:

$$\min E(x_{it}) = \min \left(\sum_{t=1}^T \sum_{i=1}^n p_{it} \cdot x_{it} \right), \quad (1)$$

$$\min F(x_{it}) = \min \left(\sum_{t=1}^T \sum_{i=1}^n r_i \cdot x_{it} \right), \quad (2)$$

$$\text{s.t., } (0 \leq x_{it} \leq c_{it}), \quad \forall i, t, \quad (3)$$

$$\sum_{i=1}^n x_{it} = D_t, \quad \forall i. \quad (4)$$

Formula (1) minimizes the total purchasing costs of materials for all customers' orders. Formula (2) minimizes the total purchasing risks (e.g., delay risk and defect risk). Formula (3) represents that the order quantities are not more than the supplier's maximum capacity in any purchasing periods. Formula (4) requires that the supply must satisfy the demands of manufacturers.

3. Methodologies for Supplier Selection and Order Allocation

This paper proposes an effective supplier selection (ranking) and order allocation (SSOA) model based on the FEAHP and dynamic programming (DP). This model comprises an FEAHP-based supplier/criteria ranking process and a DP-based order allocation process (Figure 1).

The details of the SSOA model are described as follows.

3.1. The FEAHP Method. The AHP has been widely used to address multicriteria decision-making problems. It only requires a discrete scale from one to nine. However, human judgement is uncertain of criteria's preferences. The linguistic assessment of human feelings and judgement is vague and cannot be represented reasonably in precise numbers. Hence, triangular fuzzy numbers are used to decide the priority of decision variables. Synthetic extent analysis is used to decide the final priority weights based on triangular fuzzy numbers.

3.1.1. Triangular Fuzzy Numbers and Representation of Preferences. A fuzzy set [35, 36] is characterized by a membership function, which assigns to each object a grade of membership ranging from 0 to 1. The general terms "large", "medium" and "small" are used in fuzzy set to capture a range of numerical values. If l , m , and u , respectively, denote the smallest possible value, the most promising value, and the largest possible value that describe a fuzzy event, the triangular fuzzy number (TFN) can be denoted as a vector (l, m, u) , where $l \leq m \leq u$. When $l = m = u$, it is a nonfuzzy number by convention. The membership function can be defined as

$$\mu(x | M) = \begin{cases} \frac{(x-l)}{(m-l)}, & l \leq x \leq m, \\ \frac{(u-x)}{(u-m)}, & m \leq x \leq u, \\ 0 & \text{otherwise.} \end{cases} \quad (5)$$

TFNs M_1 , M_3 , M_5 , M_7 , and M_9 are used to represent the pairwise comparison of decision variables from "equal" to "absolutely preferred", and TFNs M_2 , M_4 , M_6 , and M_8 represent the middle preference values among them. Figure 2

TABLE 1: Triangular fuzzy numbers.

Linguistic variables	Positive triangular fuzzy number	Positive reciprocal triangular fuzzy number
Extremely strong	(8, 9, 9)	(1/9, 1/9, 1/8)
Intermediate	(7, 8, 9)	(1/9, 1/8, 1/7)
Very strong	(6, 7, 8)	(1/8, 1/7, 1/6)
Intermediate	(5, 6, 7)	(1/7, 1/6, 1/5)
Strong	(4, 5, 6)	(1/6, 1/5, 1/4)
Intermediate	(3, 4, 5)	(1/5, 1/4, 1/3)
Moderately strong	(2, 3, 4)	(1/4, 1/3, 1/2)
Intermediate	(1, 2, 3)	(1/3, 1/2, 1)
Equally strong	(1, 1, 2)	(1/2, 1, 1)

shows the membership functions of the TFNs, $M_i = (l_i, m_i, u_i)$, where $i = 1, 2, \dots, 9$, and l_i, m_i, u_i are the lower, middle, and upper values of the fuzzy number M_i , respectively.

3.1.2. Fuzzy Extent Analytic Hierarchy Process (FEAHP). The FEAHP was originally introduced by Chang (1996). Some calculation steps are essential and explained as follows.

Let $X = \{x_1, x_2, x_3, \dots, x_n\}$ be an object set and $G = \{g_1, g_2, g_3, \dots, g_n\}$ a goal set. According to Chang's method, each object is taken, and extent analysis of each goal is performed. Therefore, m extent analysis values for each object can be obtained with the following signs: $M_{g_i}^1, M_{g_i}^2, \dots, M_{g_i}^m$, $i = 1, 2, \dots, n$, where $M_{g_i}^j$ ($j = 1, 2, \dots, m$) are the triangular fuzzy numbers (TFNs).

Step 1. Constructing a hierarchical structure with decision elements, decision-makers are required to make pairwise comparisons between decision alternatives and criteria using a nine-point scale (Table 1). All matrices are developed, and all pairwise comparisons are obtained from each decision-maker.

Step 2. The fuzzy synthetic extent value with respect to the i th object is defined as:

$$S_j = \sum_{j=1}^m M_{g_i}^j \times \left[\sum_{i=1}^n \sum_{j=1}^m M_{g_i}^j \right]^{-1}. \quad (6)$$

To obtain $\sum_{j=1}^m M_{g_i}^j$, the fuzzy addition operation of m extent analysis values for a particular matrix is performed as

$$\sum_{j=1}^m M_{g_i}^j = \left(\sum_{j=1}^m l_j, \sum_{j=1}^m m_j, \sum_{j=1}^m u_j \right). \quad (7)$$

To obtain $[\sum_{i=1}^n \sum_{j=1}^m M_{g_i}^j]$, the fuzzy addition operation of $M_{g_i}^j$ ($j = 1, 2, \dots, m$) values is performed as

$$\sum_{i=1}^n \sum_{j=1}^m M_{g_i}^j = \left(\sum_{i=1}^n l_i, \sum_{i=1}^n m_i, \sum_{i=1}^n u_i \right). \quad (8)$$

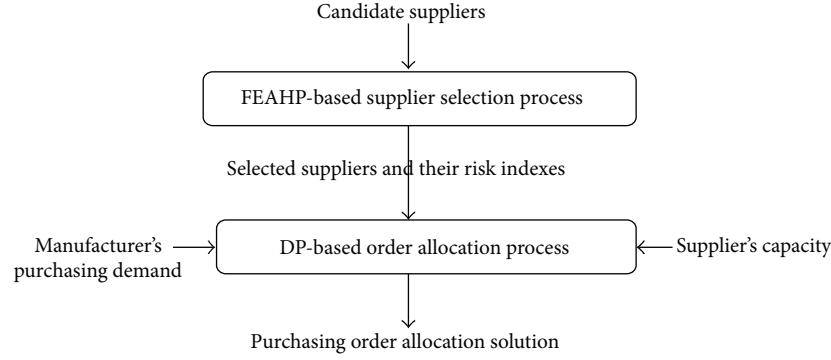


FIGURE 1: The processes of SSOA.

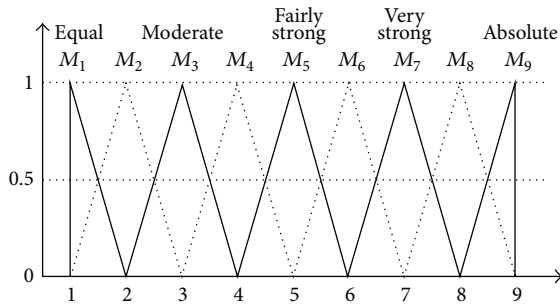
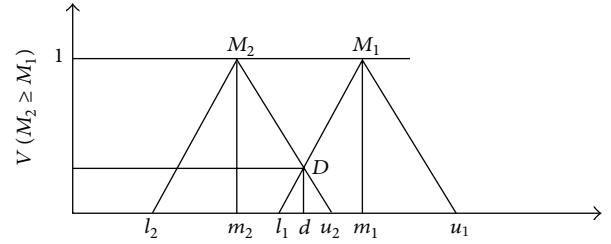


FIGURE 2: The membership functions of triangular fuzzy numbers.

FIGURE 3: The intersection between M_1 and M_2 .

And the inverse of the previous vector is computed as

$$\left[\sum_{i=1}^n \sum_{j=1}^m M_{g_i}^j \right]^{-1} = \left(\frac{1}{\sum_{i=1}^n u_i}, \frac{1}{\sum_{i=1}^n m_i}, \frac{1}{\sum_{i=1}^n l_i} \right). \quad (9)$$

Step 3. As $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are two triangular fuzzy numbers, the degree of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ possibility is defined as

$$V(M_2 \geq M_1) = \sup_{y \geq x} \{ \min(\mu_{M_1}(x), \mu_{M_2}(y)) \} \quad (10)$$

can be expressed as follows:

$$\begin{aligned} V(M_2 \geq M_1) &= \text{hgt}(M_2 \cap M_1) = \mu_{M_2}(d) \\ &= \begin{cases} 1, & \text{if } m_2 \geq m_1, \\ \left| \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \right|, & \text{otherwise.} \end{cases} \end{aligned} \quad (11)$$

Equation (11) (Figure 3) indicates that d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} . To compare M_1 and M_2 , the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are needed.

Step 4. The degree of possibility that the convex fuzzy number is greater than k convex fuzzy M_i ($i = 1, 2, \dots, k$) numbers can be defined by

$$\begin{aligned} V(M \geq M_1, M_2, \dots, M_k) &= V[(M \geq M_1) \text{ and } (M \geq M_2), \dots, \text{and } (M \geq M_k)] \\ &= \min V(M \geq M_i), \quad (i = 1, 2, 3, \dots, k). \end{aligned} \quad (12)$$

Assume that $d(A_i) = \min V(S_i \geq S_k)$ for $k = 1, 2, \dots, n$; $k \neq 1$. Then, the weight vector is given by

$$W' = (d'(A_1), d'(A_2), \dots, d'(A_n))^T, \quad (13)$$

where A_i ($i = 1, 2, 3, \dots, n$) are n elements.

Step 5. Via normalization, the normalized weight vectors are

$$W = (d(A_1), d(A_2), \dots, d(A_n))^T, \quad (14)$$

where W is a nonfuzzy number.

The upward composition of these weights (from the lowest to the top level) generates the ranking scores (weights) of elements at the lowest level (i.e., suppliers) in fulfilling the topmost objective (i.e., suppliers ranking).

3.1.3. FEAHP-Based Supplier Ranking. As discussed in the introduction, supplier ranking gives decision-makers an

effective technique to choose suitable suppliers. In this research, supplier ranking is implemented by the FEAHP method. The procedure is detailed as follows.

Step 1 (define criteria for supplier selection). To define effective criteria for supplier selection, this research collects promising candidate criteria based on existing research results (Dickson 1966; Chan and Kumar [11] 2007), and any additional criteria deemed important for manufacturers are included.

On the basis of the candidate criteria selected, structured interviews are used to evaluate these criteria by three senior specialists, including a senior designer and two purchasing managers denoted by (R1), (R2), and (R3), respectively. To evaluate candidate criteria, the respondents are requested to use the linguistic assessment of human feelings (Table 1). Upon receiving the inputs of the respondents, the criteria are identified and averaged. If there are too many criteria, the pairwise comparison can become a difficult and time-consuming process. To overcome these problems, the criteria's average value in top 5 is selected. In this paper, the 5 final criteria are (1) overall cost of products (C_1); (2) quality of product (C_2); (3) risk factors (C_3); (4) a supplier's profile (C_4); (5) service performance of a supplier (C_5).

Step 2 (define subcriteria for supplier selection). To evaluate suppliers more precisely, each selected criterion in Step 1 needs to be further represented by several subcriteria. The identification and selection of these subcriteria can be implemented as described in Step 1. If the subcriteria are still obscure, they can be re-represented by sub-subcriteria using the same process.

Step 3 (structure the hierarchical model and each criterion's weight). In this step, the FEAHP hierarchy model is built, and the weight of each supplier selection model is calculated. The developed FEAHP model, based on the identified criteria, subcriteria and subcriteria's subcriteria, has five levels: goals, criteria, subcriteria, subcriteria's subcriteria, and candidates. Figure 4 shows the 5-level hierarchy for supplier selection. The goal of supplier selection for manufacturers is identified on the first level. The second level (criteria) contains 5 criteria mentioned in Step 1. The third and fourth levels consist of subcriteria and subcriteria's subcriteria (subcriteria's subcriteria are not considered in this paper's numerical experimentation). The lowest level of the hierarchy contains alternatives. That is, different suppliers are evaluated in order to pick the best ones. As shown in Figure 4, different suppliers are used to represent the arbitrary ones which manufacturers wish to evaluate.

The FEAHP model (Figure 4) is generally applicable to any type of supplier selection by manufacturers as it covers many important factors and their related criteria, subcriteria, and subcriteria's subcriteria.

In order to obtain the priority weight of each criterion on each level, a second structure is done in a similar manner as Step 1. The interview consisting of factors on each level of the FEAHP model is used to collect the judgments of

pairwise comparisons from all evaluation team members. This judgments is performed using pairwise comparisons, which are elaborated in Section 3.1.1. An example of the pairwise comparison matrix is shown in Table 2.

Step 4 (measure supplier performance and identify supplier priority). After obtaining the priority weight of each criterion and subcriterion, the third structured interview is designed and modified. This interview collects the weights of alternatives to identify the best suppliers.

The priority weight is determined for alternatives in this step. The competitive rivals that are supposed to be suppliers for manufacturers are compared by each subcriteria standard. After finding the local weight of each alternative in subcriteria, the global weight of each alternative in each criterion can be calculated. The evaluation of the global weight of each alternative can be obtained by multiplying the global weights of subcriteria and the local weight of each alternative. Based on the global priority, the weight of each alternative can be evaluated and summarized. An example of FEAHP-based supplier ranking is described in Section 4.1.2.

3.2. Dynamic Programming. As purchasing price is time-varying in the model, the cost objective is judiciously captured by the following dynamic value function:

$$V_{1,t} = \min_{0 \leq x_{it} \leq c_{it}} \left\{ \sum_{i=1}^n p_{it} x_{it} + V_{1,t+1} \left(D_t - \sum_{i=1}^n x_{it} \right) \right\}, \quad (15)$$

where stage is decision dates in time periods, $t = 1, 2, \dots, T$. The decision variable is the quantities ordered from supplier i , $x_{it} = 0, 1, \dots, c_{it}$.

To account for both objectives, a distance-to-ideal framework is employed to integrate the risk and cost objective functions, using the optimal values of individual objectives obtained earlier.

To incorporate the ideal values of risk and cost, the sum (weights) of deviations from such ideal values is minimized. Hence, a dynamic value function is derived as follows:

$$V_{2,t} = \min_{0 \leq x_{it} \leq c_{it}} \left\{ w_{c_1} \sum_{i=1}^n p_{it} x_{it} + w_{c_3} \sum_{i=1}^n \frac{x_{it}}{w_i} + V_{2,t+1} \left(D_t - \sum_{i=1}^n x_{it} \right) \right\}, \quad (16)$$

where $V_{2,t}$ is the minimum total weighted deviation. w_{c_1} is the cost weight defined by decision-makers using the FEAHP. w_{c_3} is the risk weight defined by decision-makers using the FEAHP.

4. Numerical Experiments

To validate the effectiveness of the proposed SSOA model, a series of experiments are conducted to obtain industrial data from an apparel manufacturer. The manufacturer needs to purchase a specified amount of raw fabric from 3 appropriate material suppliers for the production of its customers' orders.

TABLE 2: The fuzzy evaluation of criteria of the overall objective.

	C_1	C_2	C_3	C_4	C_5	Weights
C_1	(1, 1, 1)	(2, 3, 4)	(3, 4, 5)	(5, 6, 7)	(2, 3, 4)	0.43
C_2	(0.25, 0.33, 0.5)	(1, 1, 1)	(3, 4, 5)	(2, 3, 4)	(4, 5, 6)	0.33
C_3	(0.2, 0.25, 0.33)	(0.2, 0.25, 0.33)	(1, 1, 1)	(3, 4, 5)	(2, 3, 4)	0.13
C_4	(0.14, 0.17, 0.2)	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(1, 1, 1)	(2, 3, 4)	0.02
C_5	(0.25, 0.33, 0.5)	(0.17, 0.2, 0.25)	(0.25, 0.33, 0.5)	(0.25, 0.33, 0.5)	(1, 1, 1)	0.09

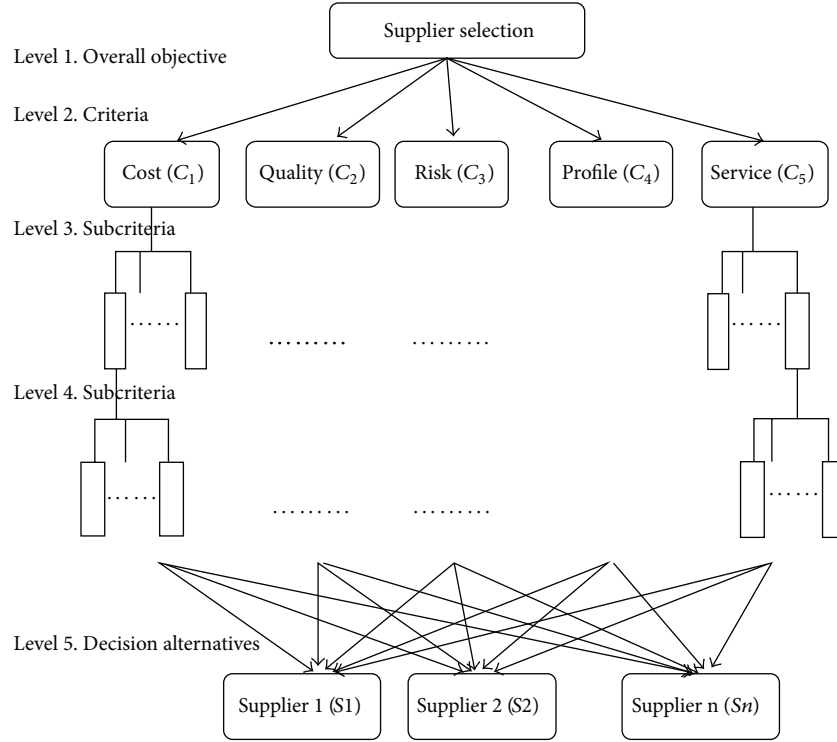


FIGURE 4: General hierarchy for supplier selection.

The 3 suppliers have been selected from its N collaborative suppliers. The manufacturer seeks to determine how much should be purchased from the 3 key suppliers in order to minimize its overall cost and maximize its utility over a multiperiod planning horizon.

4.1. Experiment for FEAHP-Based Supplier Ranking. The FEAHP starts from the pairwise comparison matrices of five criteria (Table 2). Based on these matrices, the weights of suppliers and criteria are calculated and presented in Table 3. The supplier's information and manufacturer's demands are shown in Tables 4 and 5, respectively. The solutions to single objectives are shown in Table 6, where cost is minimum. Table 7 shows the order allocation based on minimum risk.

This paper presents the results of 6 experiments.

The criteria for selection of global suppliers are as follows:

- (i) overall cost of products (C_1): product price (A_1), freight cost (A_2), penalty for delayed payment (A_3), and tariff and custom duties (A_4);

- (ii) product quality (C_2): rejection rate (A_5), response to changes (A_6), and rate of warranty claims (A_7);
- (iii) risk factors (C_3): lead time (A_8), political stability (A_9), geographical location (A_{10}), and inability to meet further requirements (A_{11});
- (iv) supplier's profile (C_4): financial status (A_{12}), performance history (A_{13}), and production capacity (A_{14});
- (v) service performance of suppliers (C_5): remedy for quality problems (A_{15}) and delivery schedule (A_{16}).

These criteria can be found in the hierarchical structure shown in Figure 5.

4.1.1. Determination of Criteria and Subcriteria Weights. The example of the pairwise comparison matrices shows that the fifth row and column attach importance to the row's criterion relative to the column's criterion (Table 2).

Due to a good cost performance, the criterion for the first row is slightly preferred to the one on product quality, risk

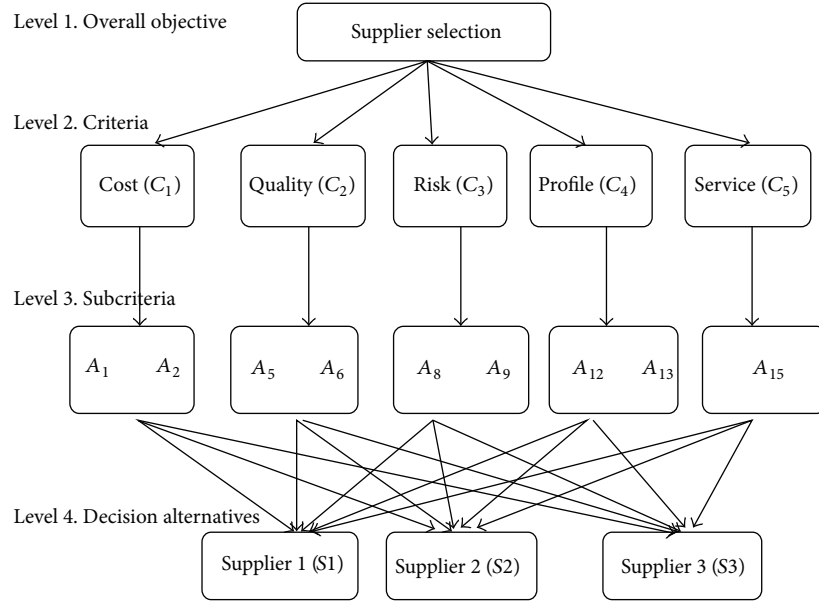


FIGURE 5: Hierarchy for supplier selection.

TABLE 3: The fuzzy evaluation of the attributes of criterion C_1 .

	A_1	A_2	A_3	A_4	Weights
A_1	(1, 1, 1)	(2, 3, 4)	(3, 4, 5)	(3, 4, 5)	0.49
A_2	(0.25, 0.33, 0.5)	(1, 1, 1)	(3, 4, 5)	(2, 3, 4)	0.31
A_3	(0.2, 0.25, 0.33)	(0.2, 0.25, 0.33)	(1, 1, 1)	(3, 4, 5)	0.09
A_4	(0.2, 0.25, 0.33)	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(1, 1, 1)	0.11

TABLE 4: The fuzzy evaluation of the attributes of criterion C_2 .

	A_5	A_6	A_7	Weights
A_5	(1, 1, 1)	(4, 5, 6)	(2, 3, 4)	0.55
A_6	(0.17, 0.2, 0.25)	(1, 1, 1)	(3, 4, 5)	0.19
A_7	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(1, 1, 1)	0.26

factors, and service performance of suppliers (the fuzzy values of (2, 3, 4), (3, 4, 5), and (2, 3, 4), resp.), which is strongly preferred to the supplier's profile (the value of (5, 6, 7)). Due to a good quality performance, the criterion for the second row and column is moderately more important than the service performance of suppliers (the value of (4, 5, 6)). Having fewer risk factors, the third row's criterion is slightly preferred to a good profile (value of (3, 4, 5)). Decision makers only need to fill in the upper half of the comparison matrix by assuming that the pairwise comparison of cost and service performance is (2, 3, 4), following the pairwise comparison of service performance and cost (0.25, 0.33, 0.5). The value of (1, 1, 1) is assigned to diagonal elements.

Calculate various decision alternatives of fuzzy numbers based on Section 3 as follows:

$$\begin{aligned}
 S_{c_1} &= (13, 17, 21) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16} \right) \\
 &= (0.23, 0.37, 0.60),
 \end{aligned}$$

$$\begin{aligned}
 S_{c_2} &= (10.25, 13.33, 16.5) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16} \right) \\
 &= (0.18, 0.29, 0.47),
 \end{aligned}$$

$$\begin{aligned}
 S_{c_3} &= (6.40, 8.50, 10.67) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16} \right) \\
 &= (0.11, 0.19, 0.30),
 \end{aligned}$$

$$\begin{aligned}
 S_{c_4} &= (3.59, 4.75, 6.03) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16} \right) \\
 &= (0.06, 0.10, 0.17),
 \end{aligned}$$

$$\begin{aligned}
 S_{c_5} &= (1.92, 2.20, 2.75) \times \left(\frac{1}{56.95}, \frac{1}{45.78}, \frac{1}{35.16} \right) \\
 &= (0.03, 0.05, 0.08).
 \end{aligned}$$

(17)

Compare the following decision alternatives:

$$V(S_{c_1} \geq S_{c_2}) = 1, \quad V(S_{c_1} \geq S_{c_3}) = 1,$$

$$V(S_{c_1} \geq S_{c_4}) = 1, \quad V(S_{c_1} \geq S_{c_5}) = 1,$$

$$V(S_{c_2} \geq S_{c_1}) = 0.75, \quad V(S_{c_2} \geq S_{c_3}) = 1,$$

TABLE 5: The fuzzy evaluation of the attributes of criterion C_3 .

	A_8	A_9	A_{10}	A_{11}	Weights
A_8	(1, 1, 1)	(4, 5, 6)	(4, 5, 6)	(1, 1, 2)	0.59
A_9	(0.17, 0.2, 0.25)	(1, 1, 1)	(4, 5, 6)	(2, 3, 4)	0.39
A_{10}	(0.17, 0.2, 0.25)	(0.17, 0.2, 0.25)	(1, 1, 1)	(3, 4, 5)	0.01
A_{11}	(0.5, 1, 1)	(0.25, 0.33, 0.5)	(0.2, 0.25, 0.33)	(1, 1, 1)	0.01

TABLE 6: The fuzzy evaluation of the attributes of criterion C_4 .

	A_{12}	A_{13}	A_{14}	Weights
A_{12}	(1, 1, 1)	(3, 4, 5)	(3, 4, 5)	0.51
A_{13}	(0.2, 0.25, 0.33)	(1, 1, 1)	(3, 4, 5)	0.18
A_{14}	(0.2, 0.25, 0.33)	(0.2, 0.25, 0.33)	(1, 1, 1)	0.31

TABLE 7: The fuzzy evaluation of the attributes of criterion C_5 .

	A_{15}	A_{16}	Weights
A_{15}	(1, 1, 1)	(3, 4, 5)	0.52
A_{16}	(0.2, 0.25, 0.33)	(1, 1, 1)	0.48

$$\begin{aligned}
V(S_{c_2} \geq S_{c_4}) &= 1, & V(S_{c_2} \geq S_{c_5}) &= 1, \\
V(S_{c_3} \geq S_{c_1}) &= 0.29, & V(S_{c_3} \geq S_{c_2}) &= 0.54, \\
V(S_{c_3} \geq S_{c_4}) &= 1, & V(S_{c_3} \geq S_{c_5}) &= 1, \\
V(S_{c_4} \geq S_{c_1}) &= 0.27, & V(S_{c_4} \geq S_{c_2}) &= 0.05, \\
V(S_{c_4} \geq S_{c_3}) &= 0.42, & V(S_{c_4} \geq S_{c_5}) &= 1, \\
V(S_{c_5} \geq S_{c_1}) &= 0.87, & V(S_{c_5} \geq S_{c_2}) &= 0.72, \\
V(S_{c_5} \geq S_{c_3}) &= 0.33, & V(S_{c_5} \geq S_{c_4}) &= 0.21.
\end{aligned} \tag{18}$$

Calculate the following decision alternatives' weights:

$$\begin{aligned}
d'(c_1) &= \min(1, 1, 1, 1) = 1, \\
d'(c_2) &= \min(0.75, 1, 1, 1) = 0.75, \\
d'(c_3) &= \min(0.29, 0.54, 1, 1) = 0.29, \\
d'(c_4) &= \min(0.27, 0.05, 0.42, 1) = 0.05, \\
d'(c_5) &= \min(0.87, 0.72, 0.33, 0.21) = 0.21.
\end{aligned} \tag{19}$$

Priority weights form $W' = (1, 0.75, 0.29, 0.05, 0.21)$ vector. Normalizing the W' vector:

$$\begin{aligned}
w_1 &= \frac{1}{1 + 0.75 + 0.29 + 0.05 + 0.21} = 0.43, \\
w_2 &= \frac{0.75}{1 + 0.75 + 0.29 + 0.05 + 0.21} = 0.33,
\end{aligned}$$

$$\begin{aligned}
w_3 &= \frac{0.29}{1 + 0.75 + 0.29 + 0.05 + 0.21} = 0.13, \\
w_4 &= \frac{0.05}{1 + 0.75 + 0.29 + 0.05 + 0.21} = 0.02, \\
w_5 &= \frac{0.21}{1 + 0.75 + 0.29 + 0.05 + 0.21} = 0.09.
\end{aligned} \tag{20}$$

After normalization of the values, priority weights of the main goal are calculated as (0.43, 0.33, 0.13, 0.02, 0.09). The results (principal vectors) show that the criteria have the following approximate priority weights: cost (0.43), quality (0.33), risk (0.13), supplier's profile (0.02) and service performance of suppliers (0.09).

Different attributes are compared by each criterion separately with the same procedure as discussed above. The fuzzy evaluation matrices of attributes and the weight vectors of subcriteria are shown in Tables 3, 4, 5, 6, and 7.

4.1.2. Calculate the Suppliers' Weights. Similarly, the fuzzy evaluation matrices of decision alternatives and the corresponding weight vector of each alternative with respect to the corresponding attributes are determined. The priority weights of suppliers with respect to each criterion are given by adding each supplier's weight to each corresponding attribute's weight. The results are shown in Tables 8, 9, 10, 11, and 12.

Finally, the priority weight of each supplier can be calculated by multiplying the weight of each corresponding criterion. The results are shown in Table 13. The summary of the overall attributes is shown in Table 13. It should be noted that among the three given suppliers, "S1" has the highest weight and therefore is selected as the best supplier to satisfy the goals and objectives of the manufacturing company. Table 13 also shows the final score of each supplier's results and rankings. As can be seen, S1 (0.5) scores higher than S2 (0.23) and S3 (0.23). The important results are shown in Figures 6 and 7.

4.2. Experiment for Dynamic Order Allocation. A real apparel manufacturer purchasing environment usually has the following four scenarios. (1) A manufacturer's demand for common material is the same in all planning periods; in order to obtain orders steadily, suppliers reserve a certain capacity and offer a reasonable price. (2) Demands for common material are steady, but suppliers do not reserve a certain capacity; so, price and capacity fluctuate in different planning periods. (3) Suppliers' prices are different throughout the planning

TABLE 8: The fuzzy evaluation of the subcriteria of criterion C_1 .

	A_1	A_2	A_3	A_4	Alternative priority weight
Weight	0.49	0.31	0.09	0.11	
Alternatives					
S1	0.51	0.51	0.69	0.87	0.57
S2	0.23	0.23	0.08	0.01	0.19
S3	0.26	0.26	0.23	0.12	0.24

TABLE 9: The fuzzy evaluation of the subcriteria of criterion C_2 .

	A_5	A_6	A_7	Alternative priority weight
Weight	0.55	0.19	0.26	
Alternatives				
S1	0.42	0.49	0.53	0.46
S2	0.28	0.23	0.15	0.24
S3	0.30	0.28	0.32	0.30

TABLE 10: The fuzzy evaluation of the subcriteria of criterion C_3 .

	A_8	A_9	A_{10}	A_{11}	Alternative priority weight
Weight	0.59	0.39	0.01	0.01	
Alternatives					
S1	0.51	0.53	0.69	0.68	0.52
S2	0.21	0.23	0.08	0.11	0.22
S3	0.28	0.24	0.23	0.21	0.26

TABLE 11: The fuzzy evaluation of the subcriteria of criterion C_4 .

	A_{12}	A_{13}	A_{14}	Alternative priority weight
Weight	0.51	0.18	0.31	
Alternatives				
S1	0.39	0.49	0.51	0.45
S2	0.28	0.21	0.17	0.23
S3	0.33	0.30	0.32	0.32

TABLE 12: The fuzzy evaluation of the subcriteria of criterion C_5 .

	A_{15}	A_{16}	Alternative priority weight
Weight	0.52	0.48	
Alternatives			
S1	0.39	0.35	0.37
S2	0.33	0.41	0.37
S3	0.28	0.24	0.26

period. (4) Suppliers' capacities and prices are different throughout the planning periods.

4.2.1. Scenario 1: Suppliers Can Reserve a Certain Capacity and Offer a Reasonable Price in All Planning Periods. After getting the weight score of each supplier and criterion in the first stage, $w_{c_1} = 0.43$ and $w_{c_2} = 0.13$. In addition to having the capacity and price information on each supplier, the

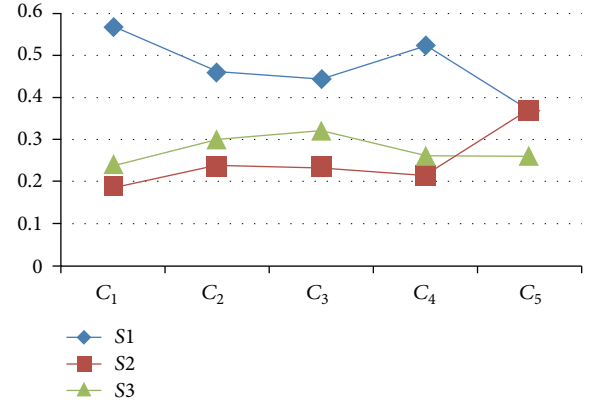


FIGURE 6: The suppliers based on the criteria.

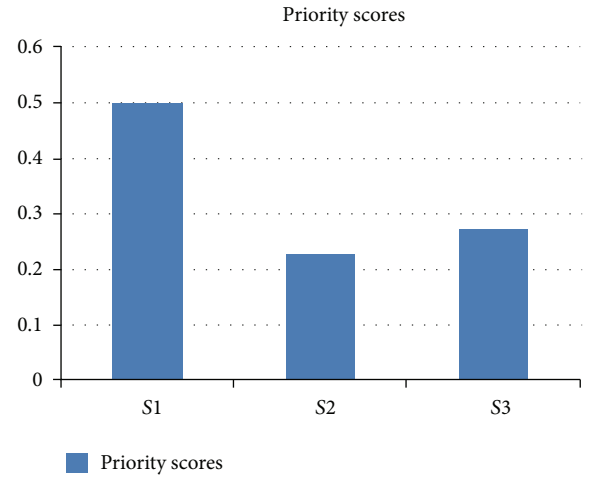


FIGURE 7: Final priority weights of the suppliers.

dynamic approach mentioned in Section 3.2 can be rewritten as follows:

$$V_{2,t} = \min_{0 \leq x_{it} \leq c_{it}} \left\{ 0.43 \sum_{i=1}^n p_{it} x_{it} + 0.13 \sum_{i=1}^n \frac{x_{it}}{w_i} + V_{2,t+1} \left(D_t - \sum_{i=1}^n x_{it} \right) \right\}. \quad (21)$$

If the manufacturer entirely just focuses on minimizing cost alone, the risk will increase substantially by 215%

TABLE 13: Demand information.

Period	1	2	3
Demand	6	6	6

TABLE 14: Price and capacity information.

Supplier	Ordering price (per unit)			Capacity
	Period 1	Period 2	Period 3	
S1	12	12	12	6
S2	10	10	10	6
S3	11	11	11	6

TABLE 15: Optimal order quantities with respect to minimum risk.

Period	1	2	3	Total risk	Total cost
S1	6	6	6	30	216
S2					
S3					

TABLE 16: Optimal order quantities with respect to minimum cost.

Period	1	2	3	Total risk	Total cost
S1				94.7	180
S2	6	6	6		
S3					

TABLE 17: Optimal order quantity with respect to minimum cost and risk.

Period	1	2	3	Total risk	Total cost
S1	4	3	2	58	205
S2	1		1		
S3	1	3	3		

than entirely focusing on minimizing risk. On the opposite extreme, if the manufacturer just entirely focuses on minimizing risk, this would raise its cost by 20% than just entirely focuses on minimizing cost only.

By applying the bi-objective dynamic function, the trade-off solution incurs at 13.9% and 94% higher than the objective of minimizing cost and minimizing risk respectively. These experimental results show that the proposed dynamic programming approach can generate a better trade-off solution than entirely focusing on minimizing cost and minimizing risk alone. (Tables 13, 14, 15, 16, and 17).

4.2.2. Scenario 2: Suppliers Have Different Capacities and Offer Different Prices in Different Planning Periods. After getting the weight score of each supplier and criterion in the first stage, $w_{c_1} = 0.43$ and $w_{c_2} = 0.13$. In addition to having the capacity and price information on each supplier, the

TABLE 18: Demand information.

Period	1	2	3
Demand	6	6	6

TABLE 19: Price and capacity information.

Supplier	Ordering price (per unit)			Capacity
	Period 1	Period 2	Period 3	
S1	12	11	14	5
S2	11	12	10	6
S3	9	11	10	4

TABLE 20: Optimal order quantities with respect to minimum risk.

Period	1	2	3	Total risk	Total cost
S1	6	6	6	30	222
S2					
S3					

TABLE 21: Optimal order quantities with respect to minimum cost.

Period	1	2	3	Total risk	Total cost
S1		5		72.24	184
S2	2		2		
S3	4	1	4		

dynamic approach mentioned in Section 3.2 can be rewritten as follows:

$$V_{2,t} = \min_{0 \leq x_{it} \leq c_{it}} \left\{ 0.43 \sum_{i=1}^n p_{it} x_{it} + 0.13 \sum_{i=1}^n \frac{x_{it}}{w_i} + V_{2,t+1} \left(D_t - \sum_{i=1}^n x_{it} \right) \right\}. \quad (22)$$

If the manufacturer entirely just focuses on minimizing cost alone, the risk will increase substantially by 141% than entirely focusing on minimizing risk. On the opposite extreme, if the manufacturer just entirely focuses on minimizing risk, this would raise its cost by 20.7% than just entirely focuses on minimizing cost only.

By applying the bi-objective dynamic function, the trade-off solution incurs at 9.2% and 77% higher than the objective of minimizing cost and minimizing risk respectively. These experimental results show that the proposed dynamic programming approach can generate a better trade-off solution than entirely focusing on minimizing cost and minimizing risk alone. (Tables 18, 19, 20, 21, and 22).

If the manufacturer entirely just focuses on minimizing cost alone, the risk will increase substantially by 61.1% than entirely focusing on minimizing risk. On the opposite extreme, if the manufacturer just entirely focuses on minimizing risk, this would raise its cost by 12.2% than just entirely focuses on minimizing cost only.

By applying the bi-objective dynamic function, the trade-off solution incurs at 4.1% and 17.8% higher than the objective of minimizing cost and minimizing risk respectively. These

TABLE 22: Optimal order quantity with respect to minimum cost and risk.

Period	1	2	3	Total risk	Total cost
S1	3	5	3	53.1	201
S2			3		
S3	3	1			

TABLE 23: Demand information.

Period	1	2	3	4
Demand	6	6	6	6

TABLE 24: Price and capacity information.

Supplier period	Ordering price (per unit)				Capacity
	1	2	3	4	
S1	12	11	14	10	5
S2	11	12	10	11	6
S3	9	11	10	11	4

TABLE 25: Optimal order quantities with respect to minimum risk.

Period	1	2	3	4	Total risk	Total cost
S1	5	5	5	5	54.76	276
S2						
S3	1	1	1	1		

TABLE 26: Optimal order quantities with respect to minimum cost.

Period	1	2	3	4	Total risk	Total cost
S1		5			88.21	246
S2			6	6		
S3	6	1				

TABLE 27: Optimal order quantity with respect to minimum cost and risk.

Period	1	2	3	4	Total risk	Total cost
S1	5	5		5	64.48	256
S2			2			
S3	1	1	4	1		

experimental results show that the proposed dynamic programming approach can generate a better trade-off solution than entirely focusing on minimizing cost and minimizing risk alone. (Tables 23, 24, 25, 26, and 27).

4.2.3. Scenario 3: The Manufacturer's Demands and the Supplier's Prices Are Different throughout the Planning Periods. After getting the weight score of each supplier and criterion in the first stage, $w_{c_1} = 0.43$ and $w_{c_2} = 0.13$. In addition to having the capacity and price information on each supplier, the

TABLE 28: Demand information.

Period	1	2	3
Demand	11	9	10

TABLE 29: Price and capacity information.

Supplier	Ordering price (per unit)			Capacity
	Period 1	Period 2	Period 3	
S1	95	95	99	4
S2	87	87	89	4
S3	93	91	91	6

TABLE 30: Optimal order quantities with respect to minimum risk.

Period	1	2	3	Total risk	Total cost
S1	4	4	4	90.69	2802
S2	1				
S3	6	5	6		

dynamic approach mentioned in Section 3.2 can be rewritten as follows:

$$V_{2,t} = \min_{0 \leq x_{it} \leq c_{it}} \left\{ 0.43 \sum_{i=1}^n p_{it} x_{it} + 0.13 \sum_{i=1}^n \frac{x_{it}}{w_i} + V_{2,t+1} \left(D_t - \sum_{i=1}^n x_{it} \right) \right\}. \quad (23)$$

If the manufacturer entirely just focuses on minimizing cost alone, the risk will increase substantially by 28% than entirely focusing on minimizing risk. On the opposite extreme, if the manufacturer just entirely focuses on minimizing risk, this would raise its cost by 4% than just entirely focuses on minimizing cost only.

By applying the bi-objective dynamic function, the trade-off solution incurs at 1% and 16% higher than the objective of minimizing cost and minimizing risk respectively. These experimental results show that the proposed dynamic programming approach can generate a better trade-off solution than entirely focusing on minimizing cost and minimizing risk alone. (Tables 28, 29, 30, 31, and 32).

If the manufacturer entirely just focuses on minimizing cost alone, the risk will increase substantially by 32% than entirely focusing on minimizing risk. On the opposite extreme, if the manufacturer just entirely focuses on minimizing risk, this would raise its cost by 4% than just entirely focuses on minimizing cost only.

By applying the bi-objective dynamic function, the trade-off solution incurs at 1% and 15.7% higher than the objective of minimizing cost and minimizing risk respectively. These experimental results show that the proposed dynamic programming approach can generate a better trade-off solution than entirely focusing on minimizing cost and minimizing risk alone. (Tables 33, 34, 35, 36, and 37).

4.2.4. Scenario 4: Demands, Price, and Capacity Are Different throughout the Planning Periods. After getting the weight

TABLE 31: Optimal order quantities with respect to minimum cost.

Period	1	2	3	Total risk	Total cost
S1	1			116.8	2706
S2	4	4	4		
S3	6	5	6		

TABLE 32: Optimal order quantity with respect to minimum cost and risk.

Period	1	2	3	Total risk	Total cost
S1	4	4	0	105.21	2728
S2	4	4	4		
S3	3	1	6		

TABLE 33: Demand information.

Period	1	2	3	4
Demand	11	9	10	12

TABLE 34: Price and capacity information.

Supplier period	Ordering price (per unit)				Capacity
	1	2	3	4	
S1	95	95	99	96	5
S2	87	87	89	90	4
S3	93	91	91	93	6

TABLE 35: Optimal order quantities with respect to minimum risk.

Period	1	2	3	4	Total risk	Total cost
S1	5	5	5	5	121.38	3950
S2				1		
S3	6	4	5	6		

TABLE 36: Optimal order quantities with respect to minimum cost.

Period	1	2	3	4	Total risk	Total cost
S1	1			2	160.29	3816
S2	4	4	4	4		
S3	6	5	6	6		

TABLE 37: Optimal order quantity with respect to minimum cost and risk.

Period	1	2	3	4	Total risk	Total cost
S1	5	5		5	140.43	3853
S2	4	4	4	4		
S3	2		6	3		

score of each supplier and criterion in the first stage, $w_{c_1} = 0.43$ and $w_{c_2} = 0.13$. In addition to having the capacity and

TABLE 38: Demand information.

Period	1	2	3
Demand	11	9	10

TABLE 39: Price and capacity information.

Supplier period	Ordering price (per unit)			Capacity		
	1	2	3	1	2	3
S1	95	95	99	4	6	5
S2	87	87	89	4	7	7
S3	93	91	91	6	5	6

TABLE 40: Optimal order quantities with respect to minimum risk.

Period	1	2	3	Total risk	Total cost
S1	4	6	5	85.7	2818
S2	1				
S3	6	3	5		

price information on each supplier, the dynamic approach mentioned in Section 3.2 can be rewritten as follows:

$$V_{2,t} = \min_{0 \leq x_{it} \leq c_{it}} \left\{ 0.43 \sum_{i=1}^n p_{it} x_{it} + 0.13 \sum_{i=1}^n \frac{x_{it}}{w_i} + V_{2,t+1} \left(D_t - \sum_{i=1}^n x_{it} \right) \right\}. \quad (24)$$

If the manufacturer entirely just focuses on minimizing cost alone, the risk will increase substantially by 20% than entirely focusing on minimizing risk. On the opposite extreme, if the manufacturer just entirely focuses on minimizing risk, this would raise its cost by 5% than just entirely focuses on minimizing cost only.

By applying the bi-objective dynamic function, the trade-off solution incurs at 1% and 9% higher than the objective of minimizing cost and minimizing risk respectively. These experimental results show that the proposed dynamic programming approach can generate a better trade-off solution than entirely focusing on minimizing cost and minimizing risk alone. (Tables 38, 39, 40, 41, and 42).

5. Conclusions

This paper investigates the topic of multiobjective order allocation based on supplier selection in the purchasing stage with single material and multiple suppliers taken into consideration. A mathematical model for investigation is established, which considers minimizing the total cost and risk in all purchasing processes. These objectives are particularly useful for manufacturing companies to survive in a make-to-order environment and improve the performance of supply chain management.

The SSOA model comprises two processes, namely, an FEAHP-based supplier/criteria ranking process and a DP-based order allocation process. In the FEAHP process, the weight of each criterion and supplier is obtained. Based

TABLE 41: Optimal order quantities with respect to minimum cost.

Period	1	2	3	Total risk	Total cost
S1	1			103.5	2688
S2	4	7	7		
S3	6	2	3		

TABLE 42: Optimal order quantity with respect to minimum cost and risk.

Period	1	2	3	Total risk	Total cost
S1	4	2		93.2	2708
S2	4	7	4		
S3	3		6		

on their weights, the optimal order allocation solution is obtained using the DP technique.

The effectiveness of the proposed optimization model is validated by using real data from a manufacturing company. The experimental results show that the proposed model can handle order allocation effectively.

The proposed optimization model can handle order allocation based on supplier selection. Further research will consider the effects of various uncertainties on supply chain management, such as uncertain customers' orders and possible material shortages.

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