Research Article

Credibility-Based Biobjective Fuzzy Optimization for Supplier Selection Problem with Disruption

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This paper addresses a supplier selection problem in which a buyer procures multiple products from multiple suppliers under disruption risk. The problem is formulated as a new credibility-based biobjective fuzzy optimization model. In the proposed model, cost, capacity, and demand are characterized by fuzzy variables with known possibility distributions. The objectives of our model are to maximize the total quality of purchased products and minimize the expected total cost. Two credibility constraints are used to guarantee that the chance about the supplier capacity and buyer demand can satisfy the predetermined levels. The main concern in solving the optimization model is to calculate the expected value of the objective function and the credibility in the constraints. When the key parameters are mutually independent triangular fuzzy variables, the expected cost objective and credibility constraints can be transformed into their equivalent forms. Taking advantage of the structural characteristics of the equivalent model, the goal programming method is employed to solve the supplier selection model, which can be solved by conventional optimization method. At last, some numerical experiments have been performed to illustrate the effectiveness of the proposed model and solution strategy.

1. Introduction

Supplier selection is an important component of supply chain management and receives a great deal of attention with the development of economic globalization and competitive pressure. Due to the presence of outside suppliers, supply chains are subject to two sources of risk, routine operational problems and major disruptions [1]. Disruptive events mainly include both natural disasters and man-made disasters, which have caused disastrous damage to various firms or companies in different supply chains. Supplier selection with disruption refers to the fact that suppliers are assigned sequentially so that the buyer may already have one backup when its primary supplier suffers a default due to disruptive risks. The purpose of this paper is to formulate a credibility-based biobjective optimization model to mitigate disruption risks while addressing concurrently operational risks as well. According to the computational results, the decision maker can obtain a supplier-level-order assignment plan that is used

for routine operation and a mitigation scheme that would be prepared when a disruption event occurs.

Some critical parameters in the supplier selection activities are always treated as uncertain variables to meet the practical situations. For instance, if one needs to make a supplier selection plan for the next month, the capacity of each supplier, the demand of the buyer, and the acquisition cost of each product are often estimated by history statistics because of no precise a priori information. The existence of uncertainty has motivated a variety of researches to investigate the supplier selection problem by using stochastic methods. For example, Balcik and Ak [2] addressed the supplier selection problem of a relief organization in preparation for the sudden-onset disasters and developed a stochastic programming model by using a scenario-based approach to represent demand uncertainty. In order to determine the optimal set of suppliers and the aggregate order and its allocation among the suppliers, Federgruen and Yang [3] analyzed a planning model for a single buyer with uncertain

demand and multiple suppliers with random yields. Guu et al. [4] proposed the optimistic, pessimistic, and combination strategies, three different optimization models with interval coefficients to model the uncertain supplier selection problem. Hosseininasab and Ahmadi [5] introduced a two-phase procedure to determine a supplier portfolio by maximizing the expected value and development of suppliers as well as minimizing their correlated risk. Hu and Kostamis [6] discussed a manufacturer's optimal multiple sourcing strategies when he faced both reliable and unreliable suppliers under supply disruptions. Sawik [7] applied a stochastic mixed-integer programming approach to the joint supplier selection and customer order scheduling in the presence of supply chain disruption risks.

Since the pioneering work of Zadeh [8], fuzzy theory has become a strong tool to cope with possibilistic uncertainty [9–11]. A number of researchers in the literature have employed fuzzy techniques into the supplier selection process. For instance, Amid et al. [12] developed a weighted max-min fuzzy model for supplier selection problem to handle different weights of multiple criteria that were determined by the analytic hierarchy process. Arabzad et al. [13] proposed a supplier selection model where suppliers were evaluated by strengths, weaknesses, opportunities, and threats analysis in the first phase and order amounts were determined through fuzzy TOPSIS method in the second phase. Arikan [14] formulated multiple objectives linear programming problem with fuzzy demand level and fuzzy aspiration levels of objectives for selecting appropriate suppliers and solved it by a novel interactive solution procedure. Azadnia et al. [15] designed an integrated approach of rule-based weighted fuzzy method, fuzzy analytical hierarchy process, and multiobjective mathematical programming for sustainable supplier selection problem and illustrated its applicability by a case study of packaging films in food industry. Guneri et al. [16] presented an integrated fuzzy and linear programming approach for supplier selection problem. Pan et al. [17] proposed a fuzzy multiobjective model for supplier selection under considering stochastic demand and transformed the original model into a weighted max-min deterministic linear/nonlinear one to find the optimal solution. For a thorough coverage of supplier selection problem, the interested reader may refer to Chai et al. [18] and references therein.

Compared to some related studies on supplier selection problem, the main contributions of the current research include the following several aspects. Firstly, this paper formulates a novel class of biobjective supplier selection model on the basis of fuzzy optimization theory. In the literature, a variety of fuzzy supplier selection models employ the multiple criteria decision making techniques. Our adopted optimization method distinguishes this study from other fuzzy supplier selection models. Secondly, our established model considers the impact of fuzzy cost, capacity, and demand parameters on the optimal supplier-level-order strategy. Most work in this field provided the supplier selection decisions based on a limited set of scenarios, which may be frustrating once there was not enough historical data. Thirdly, the basic properties of proposed model are discussed in case that the

uncertain parameters are mutually independent triangular fuzzy variables. After that a solution method integrated with goal programming is designed to turn the original fuzzy biobjective model into the equivalent deterministic single objective one. Finally, from the application point of view, a supplier selection numerical example is presented. The computational results show the effectiveness and superiority of established biobjective fuzzy optimization model and designed solution procedure.

The rest of this paper is organized as follows. Section 2 formulates a new class of fuzzy supplier selection model. Section 3 focuses on the deterministic equivalent expressions to the expected objective and credibility constraints. In Section 4, one solution approach, preemptive goal programming method, is designed. To apply the proposed model to a decision making problem, Section 5 presents a selection example with one buyer, three products, and five suppliers. Finally, Section 6 concludes the paper and gives the future work.

2. Fuzzy Biobjective Model for Supplier Selection Problem

This section aims to use fuzzy optimization methodology to formulate a credibility-based supplier selection model. In the supplier selection decision making process, there are multiple suppliers and multiple products for a single buyer, which is faced by most purchasing organizations. In order to hedge against operational risks as well as mitigate against disruptions, all the suppliers are separated as primary suppliers and backup ones. Primary suppliers are used to sign long-term procurement contracts for routine operation, while backups will not make short-term trade-offs with the buyer unless disruptive events erupt on one or more primary suppliers. Snyder and Daskin [19] introduced the concept of level-r facility to deal with sequential assignment of facilities to customers in the facility location problem. Motivated by the above-mentioned research, in our model the primary suppliers are assigned to level-1 suppliers for the given product. The remaining backup ones are then sequentially assigned to level-2 supplier, level-3 supplier, and so on. Once a disruption occurs, the primary suppliers fail and the backup ones are used to provide order fulfillment. The model accommodates a mitigation plan through assigning suppliers at consecutive levels and an optimal order decision. The assumptions, notations used in the formulation, and the formulation process are explained as follows.

Assumptions

(A1) A joint replenishment policy is adopted for all products.

(A2) The supplier will afford products with the same quality level whenever he is a primary supplier or a backup.

(A3) The higher the level, the higher the variable cost together with longer lead time but lower fixed cost, which makes sense that the buyer will not use backup supplier unless one primary fails.

Constraint Conditions. (I) Constraint (1) ensures that each product is allowed to have at most m level-1 suppliers; that is,

$$\sum_{s \in S} x_{1sp} \leq m, \quad \forall p \in P. \tag{1}$$

(II) Constraint (2) imposes that a single product can have only one backup supplier for each level; that is,

$$\sum_{s \in S} x_{rsp} = 1, \quad \forall p \in P, \ r = 2, 3, \ldots, n - m + 1. \tag{2}$$

(III) Constraint (3) prohibits assigning one supplier to more than one level for the same product, which should be represented by

$$\sum_{r \in R} x_{rsp} = 1, \quad \forall s \in S, \ p \in P. \tag{3}$$

The aforementioned three equations (1)–(3) are the basic ideas of caving up suppliers. In our paper, the replacement scheme follows that the backup supplier with one level below will replace the failed supplier in case of a default at a primary supplier. When two primary ones are exposed to disruptive risk, both level-2 and level-3 suppliers will be employed to afford indents. Similarly, when m' ($m' \leq m$) primary ones suffer "fail," level-2 to level-m' backup suppliers, if existing, will receive tasks until all suppliers have been employed.

(IV) Constraint (4) ensures that the total lead time does not exceed the acceptable maximal lead time:

$$\sum_{s \in S} \sum_{p \in P} L_{1sp} y_{1sp} + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} L_{rsp} x_{rsp} \leq L. \tag{4}$$

(V) Constraint (5) imposes that the corresponding order sizes should be restricted to its capacity once supplier s has been a primary dealer for product p; that is,

$$\mathrm{Cr} \left\{ y_{1sp} \leq \eta_{sp} x_{1sp} \right\} \geq \alpha_{sp}, \quad \forall s \in S, \ p \in P, \tag{5}$$

where the parameter α_{sp} represents capacity level for supplier s.

(VI) Constraint (6) ensures that the order quantities received by all for some product could meet the buyer demand; that is,

$$\mathrm{Cr} \left\{ \sum_{s \in S} y_{1sp} \geq \zeta_p \right\} \geq \beta_p, \quad \forall p \in P, \tag{6}$$

where the parameter β_p represents service level for product p.

(VII) Constraints (7) guarantee that the binary and nonnegativity restrictions on the decision variables hold:

$$x_{rsp} \in \{0, 1\}, \quad \forall s \in S, \ p \in P,$$
$$y_{1sp} \geq 0, \quad \forall s \in S, \ p \in P. \tag{7}$$

Objective Functions. The first objective function is to maximize the total quality of purchased products. The total quality is divided into two parts: primary suppliers' quality and an opportunity quality; that is,

$$\max \sum_{s \in S} \sum_{p \in P} Q_{sp} y_{1sp} + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} Q_{sp} x_{rsp}, \tag{8}$$

where Q_{sp} has nothing with priority levels.

The second objective function is to minimize the total cost. The total cost is comprised of the fixed cost and variable cost. The fixed cost that the buyer spends in signing a contact with every supplier is defined as $\sum_{s \in S} \sum_{p \in P} \sum_{r=1}^{n-m+1} F_{rsp} x_{rsp}$. The variable cost including the purchasing, transportation, and holding cost from primary suppliers can be represented by $\sum_{s \in S} \sum_{p \in P} \xi_{1sp} y_{1sp}$, while the one from backup suppliers, also called an opportunity cost due to not using backup suppliers at the beginning, can be represented by $\sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \xi_{rsp} x_{rsp}$. The expected total cost can be minimized; that is,

$$\min \mathrm{E} \left\{ \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} F_{rsp} x_{rsp} + \sum_{s \in S} \sum_{p \in P} \xi_{1sp} y_{1sp} \right.$$
$$\left. + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \xi_{rsp} x_{rsp} \right\}. \tag{9}$$

Based on the above analysis, a credibility-based biobjective fuzzy supplier selection optimization model is formally built as follows:

$$\max \quad \sum_{s \in S} \sum_{p \in P} Q_{sp} y_{1sp} + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} Q_{sp} x_{rsp}$$

$$\min \quad \mathrm{E} \left\{ \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} F_{rsp} x_{rsp} + \sum_{s \in S} \sum_{p \in P} \xi_{1sp} y_{1sp} + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \xi_{rsp} x_{rsp} \right\}$$

$$\text{s.t.} \quad \sum_{s \in S} x_{1sp} \leq m, \quad \forall p \in P,$$

$$\sum_{s \in S} x_{rsp} = 1, \quad \forall p \in P, \ r = 2, 3, \ldots, n - m + 1,$$

$$\sum_{r \in R} x_{rsp} = 1, \quad \forall s \in S, \ p \in P,$$

$$\sum_{s \in S} \sum_{p \in P} L_{1sp} y_{1sp} + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} L_{rsp} x_{rsp} \leq L,$$

$$\text{Cr} \left\{ y_{1sp} \leq \eta_{sp} x_{1sp} \right\} \geq \alpha_{sp}, \quad \forall s \in S, \ p \in P,$$

$$\text{Cr} \left\{ \sum_{s \in S} y_{1sp} \geq \zeta_p \right\} \geq \beta_p, \quad \forall p \in P,$$

$$x_{rsp} \in \{0, 1\}, \quad \forall r \in R, \ s \in S, \ p \in P,$$

$$y_{1sp} \geq 0, \quad \forall s \in S, \ p \in P. \tag{10}$$

Model (10) is a biobjective mixed-integer programming with the expectation objective and credibility constraints. The general solution methods require conversion of expected value and credibility to their respective deterministic equivalent forms. Usually, this transformation is hard to perform and only successful for some special cases. In the subsequent section, the equivalent formulation of model (10) will be discussed.

3. Model Analysis

To solve model (10), the key challenges are to calculate the expected value objective in terms of the total cost and check the credibility constraints with respect to supplier capacity and service level. The main purpose of this section will consider some special cases that all fuzzy variables are triangularly distributed and concern the equivalent expressions.

Assume ξ_{rsp}, η_{sp}, and ζ_p are mutually independent triangular fuzzy variables such that their elements are defined by

$$\xi_{rsp} = \left(\xi_{rsp}^{r_1}, \xi_{rsp}^{r_2}, \xi_{rsp}^{r_3} \right),$$

$$\eta_{sp} = \left(\eta_{sp}^{r_1}, \eta_{sp}^{r_2}, \eta_{sp}^{r_3} \right), \tag{11}$$

$$\zeta_p = \left(\zeta_p^{r_1}, \zeta_p^{r_2}, \zeta_p^{r_3} \right).$$

The first theorem considers the analytical expression of total cost objective; that is,

$$\text{E} \left\{ \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} F_{rsp} x_{rsp} + \sum_{s \in S} \sum_{p \in P} \xi_{1sp} y_{1sp} \right.$$

$$\left. + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \xi_{rsp} x_{rsp} \right\}. \tag{12}$$

Theorem 1. *Consider total cost objective in supplier selection model (10). Let the fuzzy cost $\xi_{rsp} = (\xi_{rsp}^{r_1}, \xi_{rsp}^{r_2}, \xi_{rsp}^{r_3})$ for unit product p from its level-r supplier s be a triangular fuzzy variable. Suppose $\xi_{111}, \xi_{112}, \ldots, \xi_{n-m+1|S||P|}$ are mutually independent; then total cost objective is equivalent to*

$$\sum_{s \in S} \sum_{p \in P} \sum_{r \in R} F_{rsp} x_{rsp} + \sum_{s \in S} \sum_{p \in P} \frac{\xi_{1sp}^{r_1} + 2\xi_{1sp}^{r_2} + \xi_{1sp}^{r_3}}{4} y_{1sp}$$

$$+ \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \frac{\xi_{rsp}^{r_1} + 2\xi_{rsp}^{r_2} + \xi_{rsp}^{r_3}}{4} x_{rsp}. \tag{13}$$

Proof. Suppose ξ_{rsp} is a triangular fuzzy variable. Based on the definition of mathematical expectation [9], it follows that the expected value of ξ_{rsp} is

$$\text{E} \left[\xi_{rsp} \right] = \frac{\xi_{rsp}^{r_1} + 2\xi_{rsp}^{r_2} + \xi_{rsp}^{r_3}}{4}. \tag{14}$$

Since $\xi_{111}, \xi_{112}, \ldots, \xi_{n-m+1|S||P|}$ are mutually independent, due to the linearity of expectation, we have

$$\text{E} \left\{ \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} F_{rsp} x_{rsp} + \sum_{s \in S} \sum_{p \in P} \xi_{1sp} y_{1sp} \right.$$

$$\left. + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \xi_{rsp} x_{rsp} \right\} = \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} F_{rsp} x_{rsp}$$

$$+ \text{E} \left\{ \sum_{s \in S} \sum_{p \in P} \xi_{1sp} y_{1sp} + \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \xi_{rsp} x_{rsp} \right\}$$

$$= \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} F_{rsp} x_{rsp} + \sum_{s \in S} \sum_{p \in P} \mathrm{E}\left[\xi_{1sp}\right] y_{1sp}$$

$$+ \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \mathrm{E}\left[\xi_{rsp}\right] x_{rsp}.$$

(15)

Therefore, total cost objective is equivalent to

$$\sum_{s \in S} \sum_{p \in P} \sum_{r \in R} F_{rsp} x_{rsp} + \sum_{s \in S} \sum_{p \in P} \frac{\xi_{1sp}^{r_1} + 2\xi_{1sp}^{r_2} + \xi_{1sp}^{r_3}}{4} y_{1sp}$$

$$+ \sum_{s \in S} \sum_{p \in P} \sum_{r=2}^{n-m+1} \frac{\xi_{rsp}^{r_1} + 2\xi_{rsp}^{r_2} + \xi_{rsp}^{r_3}}{4} x_{rsp}.$$

(16)

The proof of theorem is complete. □

The following theorem establishes the analytical expressions of supplier capacity constraint; that is,

$$\mathrm{Cr}\left\{y_{1sp} \le \eta_{sp} x_{1sp}\right\} \ge \alpha_{sp}, \quad \forall s \in S, \ p \in P. \quad (17)$$

Theorem 2. *Consider supplier capacity constraint in supplier selection model (10). Let the fuzzy capacity $\eta_{sp} = (\eta_{sp}^{r_1}, \eta_{sp}^{r_2}, \eta_{sp}^{r_3})$ at supplier s for product p be a triangular fuzzy variable.*

(i) *If $\alpha_{sp} \in (0, 0.5)$, then supplier capacity constraint is equivalent to*

$$y_{1sp} \le \left[\eta_{sp}^{r_3} - 2\alpha_{sp}\left(\eta_{sp}^{r_3} - \eta_{sp}^{r_2}\right)\right] x_{1sp}, \quad \forall s \in S, \ p \in P. \quad (18)$$

(ii) *If $\alpha_{sp} \in [0.5, 1]$, then supplier capacity constraint is equivalent to*

$$y_{1sp} \le \left[\eta_{sp}^{r_1} + 2\left(1 - \alpha_{sp}\right)\left(\eta_{sp}^{r_2} - \eta_{sp}^{r_1}\right)\right] x_{1sp},$$

$$\forall s \in S, \ p \in P. \quad (19)$$

Proof. We only prove assertion (ii), and assertion (i) can be proved similarly.

Suppose η_{sp} is a triangular fuzzy variable. The possibility distribution of η_{sp} is

$$\mu_{\eta_{sp}}(x) = \begin{cases} \dfrac{x - \eta_{sp}^{r_1}}{\eta_{sp}^{r_2} - \eta_{sp}^{r_1}}, & \text{if } x \in \left[\eta_{sp}^{r_1}, \eta_{sp}^{r_2}\right), \\[3mm] \dfrac{\eta_{sp}^{r_3} - x}{\eta_{sp}^{r_3} - \eta_{sp}^{r_2}}, & \text{if } x \in \left[\eta_{sp}^{r_2}, \eta_{sp}^{r_3}\right]. \end{cases} \quad (20)$$

Denote $\eta = \eta_{sp} x_{1sp}$. If $\alpha_{sp} \ge 0.5$, according to credibility measure, then we have

$$\mathrm{Cr}\left\{y_{1sp} \le \eta_{sp} x_{1sp}\right\} = \mathrm{Cr}\left\{\eta \ge t\right\}$$

$$= \frac{1}{2}\left(1 + \sup_{x \ge t}\mu_{\eta}(x) - \sup_{x < t}\mu_{\eta}(x)\right) \quad (21)$$

$$= \frac{1}{2}\left(2 - \sup_{x < t}\mu_{\eta}(x)\right),$$

where $t = y_{1sp}$. Thus, $\mathrm{Cr}\{y_{1sp} \le \eta_{sp} x_{1sp}\} \ge \alpha_{sp}$ is equivalent to $\sup_{x < t}\mu_{\eta}(x) \le 2 - 2\alpha_{sp}$.

If we denote

$$\eta_{\inf}(\alpha) = \sup\left\{t \mid \sup_{x < t}\mu_{\eta}(x) \le \alpha\right\} \quad (22)$$

for $\alpha \in (0, 1]$, then we have $\eta_{\inf}(2 - 2\alpha_{sp}) \ge t$. Together with $x_{1sp} \ge 0$, it follows from the property of fractile function that

$$\eta_{\inf}\left(2 - 2\alpha_{sp}\right) = \left(\eta_{sp} x_{1sp}\right)_{\inf}\left(2 - 2\alpha_{sp}\right)$$

$$= \eta_{sp,\inf}\left(2 - 2\alpha_{sp}\right) x_{1sp} \ge y_{1sp}. \quad (23)$$

If $\alpha_{sp} \ge 0.5$, then $\eta_{sp,\inf}(2 - 2\alpha_{sp})$ is the solution of the following equation:

$$\frac{x - \eta_{sp}^{r_1}}{\eta_{sp}^{r_2} - \eta_{sp}^{r_1}} - \left(2 - 2\alpha_{sp}\right) = 0. \quad (24)$$

Solving the above equation, we have

$$\eta_{sp,\inf}\left(2 - 2\alpha_{sp}\right) = \eta_{sp}^{r_1} + 2\left(1 - \alpha_{sp}\right)\left(\eta_{sp}^{r_2} - \eta_{sp}^{r_1}\right). \quad (25)$$

Therefore, supplier capacity constraint is equivalent to

$$y_{1sp} \le \left[\eta_{sp}^{r_1} + 2\left(1 - \alpha_{sp}\right)\left(\eta_{sp}^{r_2} - \eta_{sp}^{r_1}\right)\right] x_{1sp}. \quad (26)$$

The proof of theorem is complete. □

The last theorem constructs the analytical expressions of service level constraint; that is,

$$\mathrm{Cr}\left\{\sum_{s \in S} y_{1sp} \ge \zeta_p\right\} \ge \beta_p, \quad \forall p \in P. \quad (27)$$

Theorem 3. *Consider service level constraint in supplier selection model (10). Let the fuzzy demand $\zeta_p = (\zeta_p^{r_1}, \zeta_p^{r_2}, \zeta_p^{r_3})$ for product p be a triangular fuzzy variable.*

(i) *If $\beta_p \in (0, 0.5)$, then service level constraint is equivalent to*

$$\sum_{s \in S} y_{1sp} \ge \zeta_p^{r_1} + 2\beta_p\left(\zeta_p^{r_2} - \zeta_p^{r_1}\right), \quad \forall p \in P. \quad (28)$$

(ii) *If $\beta_p \in [0.5, 1]$, then service level constraint is equivalent to*

$$\sum_{s \in S} y_{1sp} \ge \zeta_p^{r_3} - 2\left(1 - \beta_p\right)\left(\zeta_p^{r_3} - \zeta_p^{r_2}\right), \quad \forall p \in P. \quad (29)$$

Proof. We only prove assertion (i), and assertion (ii) can be proved similarly.

Suppose ζ_p is a triangular fuzzy variable. The possibility distribution of ζ_p is

$$\mu_{\zeta_p}(x) = \begin{cases} \dfrac{x - \zeta_p^{r_1}}{\zeta_p^{r_2} - \zeta_p^{r_1}}, & \text{if } x \in \left[\zeta_p^{r_1}, \zeta_p^{r_2}\right), \\[3mm] \dfrac{\zeta_p^{r_3} - x}{\zeta_p^{r_3} - \zeta_p^{r_2}}, & \text{if } x \in \left[\zeta_p^{r_2}, \zeta_p^{r_3}\right]. \end{cases} \quad (30)$$

If $\beta_p < 0.5$, then we have

$$
\begin{aligned}
\mathrm{Cr}\left\{\sum_{s\in S} y_{1sp} \geq \zeta_p\right\} &= \mathrm{Cr}\left\{\zeta_p \leq \sum_{s\in S} y_{1sp}\right\} \\
&= \frac{1}{2}\left(1 + \sup_{x\leq r}\mu_{\zeta_p}(x) - \sup_{x>r}\mu_{\zeta_p}(x)\right) \\
&= \frac{1}{2}\sup_{x\leq r}\mu_{\zeta_p}(x),
\end{aligned}
\tag{31}
$$

where $r = \sum_{s\in S} y_{1sp}$. Thus, $\mathrm{Cr}\{\sum_{s\in S} y_{1sp} \geq \zeta_p\} \geq \beta_p$ is equivalent to $\sup_{x\leq r}\mu_{\zeta_p}(x) \geq 2\beta_p$.

If we denote

$$
\zeta_{p,\inf}(\beta) = \inf\left\{r \mid \sup_{x\leq r}\mu_{\zeta_p}(x) \geq \beta\right\}
\tag{32}
$$

for $\beta \in (0, 1]$, then we have $\zeta_{p,\inf}(2\beta_p) \leq r$.

If $\beta_p < 0.5$, then $\zeta_{p,\inf}(2\beta_p)$ is the solution of the following equation:

$$
\frac{x - \zeta_p^{r_1}}{\zeta_p^{r_2} - \zeta_p^{r_1}} - 2\beta_p = 0.
\tag{33}
$$

Solving the above equation, we have

$$
\zeta_{p,\inf}(2\beta_p) = \zeta_p^{r_1} + 2\beta_p\left(\zeta_p^{r_2} - \zeta_p^{r_1}\right).
\tag{34}
$$

Therefore, service level constraint is equivalent to

$$
\sum_{s\in S} y_{1sp} \geq \zeta_p^{r_1} + 2\beta_p\left(\zeta_p^{r_2} - \zeta_p^{r_1}\right), \quad \forall p \in P.
\tag{35}
$$

The proof of theorem is complete. $\square$

4. Solution Method

The deterministic equivalent formulation of original supplier selection model is a multiobjective optimization problem. There are a great number of solution methods such as ϵ-constraint, weighted sum, lexicographic min-max method, and intelligent algorithm that have been developed for solving such problems. For example, Wang et al. [20] designed a multiobjective algorithm that integrated the guided genetic algorithm and the nondominated sorting genetic algorithm II to solve the problems of supplier selection, assembly sequence planning, and assembly line balancing. The interested readers can refer to Chinchuluun and Pardalos [21], Collette and Siarry [22], and Deb [23] for details on other solution approaches and applications of multiobjective optimization.

When planning the supplier selection system, the goals considered in the original model have economical and quality implications. Multiple goals with appropriate priority structure must be taken into consideration, so it is the best choice to employ the goal programming method to convert a multiobjective optimization model into a single objective one. The goal programming method was introduced by Charnes et al. [24], extensively discussed by Charnes and Cooper [25],

and further refined by the work of Ijiri [26] and Lee [27]. The solution process for our mixed-integer goal programming is described as follows.

Firstly, determine the preemptive level for every objective according to the decision maker's preference.

For the quality objective function, the target value G_1 is given by senior decision maker who makes the decision relying on previous information or personal preference. When the target value is fixed, additional variables d_1^+ and d_1^- can be obtained, serving as positive and negative deviation variables. Here, d_1^+ represents the segment of the first objective exceeding its target value, and d_1^- denotes the segment of the first objective less than its target value. The soft constraint is chalked up well by involving the negative and positive deviation variables together with the target value into the first objective. Note that the quality objective is required to find the maximum value. Therefore, the smaller the d_1^- is, the best the objective is:

$$
\min \quad d_1^-
$$

$$
\text{s.t.} \quad \sum_{s\in S}\sum_{p\in P} Q_{sp} y_{1sp} + \sum_{s\in S}\sum_{p\in P}\sum_{r=2}^{n-m+1} Q_{sp} x_{rsp} + d_1^- - d_1^+
$$
$$
= G_1.
\tag{36}
$$

Similarly, the total cost objective function can be written as follows:

$$
\min \quad d_2^+
$$

$$
\begin{aligned}
\text{s.t.} \quad &\sum_{s\in S}\sum_{p\in P}\sum_{r\in R} F_{rsp} x_{rsp} \\
&+ \sum_{s\in S}\sum_{p\in P} \frac{\xi_{1sp}^{r_1} + 2\xi_{1sp}^{r_2} + \xi_{1sp}^{r_3}}{4} y_{1sp} \\
&+ \sum_{s\in S}\sum_{p\in P}\sum_{r=2}^{n-m+1} \frac{\xi_{rsp}^{r_1} + 2\xi_{rsp}^{r_2} + \xi_{rsp}^{r_3}}{4} x_{rsp} + d_2^- - d_2^+ \\
&= G_2.
\end{aligned}
\tag{37}
$$

The decision maker assigns these two objectives with preemptive levels P_1 and P_2, complying with $P_1 \gg P_2$. That is to say, when formulating the criteria function, it is requested to order the unfavorable deviations into a number of preemptive levels, with the minimization of a deviation in a higher preemptive level being infinitely more important than any deviations in lower preemptive levels. Assume the cost objective is prior to the quality objective. The criteria function minimizes the sum of the deviations from the target values specified in the soft constraints appended above:

$$
\min P_1 d_1^- + P_2 d_2^+.
\tag{38}
$$

Secondly, specify the domain for capacity parameter α_{sp} and service level β_p.

On the basis of Theorem 2, if $\alpha_{sp} \geq 0.5$ and η_{sp} is triangularly distributed, then the supplier capacity constraint

$$
\mathrm{Cr}\left\{y_{1sp} \leq \eta_{sp} x_{1sp}\right\} \geq \alpha_{sp}, \quad \forall p \in P,
\tag{39}
$$

has the following equivalent expression:

$$y_{1sp} \le \left[\eta_{sp}^{r_1} + 2\left(1 - \alpha_{sp}\right)\left(\eta_{sp}^{r_2} - \eta_{sp}^{r_1}\right)\right] x_{1sp},$$
$$\forall s \in S, \; p \in P. \tag{40}$$

According to Theorem 3, if $\beta_p \ge 0.5$ and ζ_p is a triangular fuzzy variable, then the service level constraint

$$\mathrm{Cr}\left\{\sum_{s \in S} y_{1sp} \ge \zeta_p\right\} \ge \beta_p, \quad \forall p \in P, \tag{41}$$

is equivalent to the following inequality:

$$\sum_{s \in S} y_{1sp} \ge \zeta_p^{r_3} - 2\left(1 - \beta_p\right)\left(\zeta_p^{r_3} - \zeta_p^{r_2}\right), \quad \forall p \in P. \tag{42}$$

Thirdly, solve the deterministic mixed-integer goal programming model.

The preemptive goal programming formulation of the supplier selection model is given as follows:

$$\min \quad P_1 d_1^- + P_2 d_2^+$$

$$\text{s.t.} \quad \sum_{s \in S}\sum_{p \in P} Q_{sp} y_{1sp} + \sum_{s \in S}\sum_{p \in P}\sum_{r=2}^{n-m+1} Q_{sp} x_{rsp} + d_1^- - d_1^+$$

$$= G_1,$$

$$\sum_{s \in S}\sum_{p \in P}\sum_{r \in R} F_{rsp} x_{rsp}$$

$$+ \sum_{s \in S}\sum_{p \in P} \frac{\xi_{1sp}^{r_1} + 2\xi_{1sp}^{r_2} + \xi_{1sp}^{r_3}}{4} y_{1sp}$$

$$+ \sum_{s \in S}\sum_{p \in P}\sum_{r=2}^{n-m+1} \frac{\xi_{rsp}^{r_1} + 2\xi_{rsp}^{r_2} + \xi_{rsp}^{r_3}}{4} x_{rsp} + d_2^- - d_2^+$$

$$= G_2,$$

$$\sum_{s \in S} x_{1sp} \le m, \quad \forall p \in P,$$

$$\sum_{s \in S} x_{rsp} = 1, \quad \forall p \in P, \; r = 2, 3, \ldots, n - m + 1,$$

$$\sum_{r \in R} x_{rsp} = 1, \quad \forall s \in S, \; p \in P,$$

$$\sum_{s \in S}\sum_{p \in P} L_{1sp} y_{1sp} + \sum_{s \in S}\sum_{p \in P}\sum_{r=2}^{n-m+1} L_{rsp} x_{rsp} \le L,$$

$$y_{1sp} \le \left[\eta_{sp}^{r_1} + 2\left(1 - \alpha_{sp}\right)\left(\eta_{sp}^{r_2} - \eta_{sp}^{r_1}\right)\right] x_{1sp},$$
$$\forall s \in S, \; p \in P,$$

$$\sum_{s \in S} y_{1sp} \ge \zeta_p^{r_3} - 2\left(1 - \beta_p\right)\left(\zeta_p^{r_3} - \zeta_p^{r_2}\right),$$
$$\forall p \in P,$$

TABLE 1: Quality data for supplier selection problem.

Product	Quality				
	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5
1	0.95	0.95	0.9	0.9	0.9
2	0.95	0.97	0.9	0.93	0.92
3	0.93	0.99	0.9	0.9	0.97

$$x_{rsp} \in \{0, 1\},$$

$$y_{1sp} \ge 0,$$

$$\forall r \in R, \; s \in S, \; p \in P. \tag{43}$$

Model (43) is a mixed-integer parametric programming. It can be solved by using conventional optimization algorithms when the parameters vary in their domains. For example, given the parameters α_{sp} and β_p, we can make use of the branch-and-bound method to solve it. It is known that the LINGO is a state-of-the-art commercial tool including the branch-and-bound IP code. In the next section, the effectiveness of the goal programming method can be demonstrated via numerical experiments.

However, the size of the supplier selection problem may be a serious disadvantage. As the real instance increases the number of suppliers or products, direct solution using standard software may become much less attractive due to the memory requirements. It is of special value in developing a more efficient customized algorithm designed to exploit the structure of the proposed model for large-scale instances, which is a significant avenue for further work.

5. Numerical Example

This section reports the computational results for the proposed model and solution approach.

5.1. Problem Description. Suppose that a single buyer needs to purchase three kinds of products. He has identified five potential suppliers and has classified them into three assignment levels where there are three primary suppliers. The data in respect of product quality, unit fixed cost, and lead time have been provided by Tables 1, 2, and 3. The data in terms of variable cost, supplier capacity, and buyer demand are observed from the historical data where there exist many fluctuations. They have been represented as fuzzy numbers with triangular distributions in Tables 4 and 5. The demand for three products is (140, 160, 190), (220, 250, 280), and (200, 230, 240), respectively. The buyer wants to select the primary and backup suppliers and decide the order amounts among selected suppliers so as to maximize the total quality of products and minimize the total cost of the supplier selection.

5.2. Computational Results and Discussions. When the model parameters α_{sp}, β_p, G_1, G_2, and L are set to 0.95, 0.95, 700, 6000, and 2800, respectively, we obtain the maximal

TABLE 2: Fixed cost data for supplier selection problem.

Supplier	Product 1			Product 2			Product 3		
	Level-1	Level-2	Level-3	Level-1	Level-2	Level-3	Level-1	Level-2	Level-3
1	100	95	90	75	65	60	56	50	45
2	200	160	150	150	130	120	113	108	103
3	150	130	120	113	105	95	84	70	65
4	150	135	110	120	108	100	90	85	70
5	120	112	102	90	80	60	66	60	56

TABLE 3: Lead time data for supplier selection problem.

Supplier	Product 1			Product 2			Product 3		
	Level-1	Level-2	Level-3	Level-1	Level-2	Level-3	Level-1	Level-2	Level-3
1	10	10.5	10.8	9	9.5	9.9	1	1.1	1.2
2	5	5.3	5.5	2	2.1	2.2	8	8.4	8.8
3	8	8.4	8.6	3	3.2	3.3	6	6.2	6.4
4	3	3.1	3.3	4	4.2	4.4	6	6.3	6.6
5	8	8.3	8.8	2	2.1	2.3	4	4.2	4.5

TABLE 4: Variable cost data for supplier selection problem.

Supplier	Product	Variable cost		
		Level-1	Level-2	Level-3
1	1	(9.5, 10, 10.7)	(11, 11.5, 12)	(12, 12.5, 13)
	2	(6, 7, 7.3)	(7.4, 7.5, 7.9)	(8, 8.3, 8.5)
	3	(6, 7, 7.3)	(10.5, 10.6, 11)	(11.2, 11.3, 11.6)
2	1	(9, 10, 10.5)	(10.5, 10.75, 11)	(11.2, 11.5, 11.8)
	2	(5.5, 6, 6.2)	(6.3, 6.4, 6.5)	(6.6, 6.8, 7)
	3	(5, 6, 6.3)	(6.4, 6.5, 6.7)	(6.8, 6.9, 8)
3	1	(5.8, 6, 6.35)	(6.4, 6.5, 6.8)	(6.85, 7, 7.5)
	2	(4.2, 5, 5.2)	(5.25, 5.4, 5.6)	(5.65, 5.9, 6)
	3	(2.4, 3, 3.2)	(3.25, 3.3, 3.5)	(3.5, 3.6, 4)
4	1	(9, 10, 10.2)	(10.4, 10.8, 11)	(11, 11.5, 12)
	2	(8.5, 9, 9.6)	(9.6, 9.8, 10.3)	(10.5, 10.8, 11)
	3	(4.2, 5, 5.5)	(5.5, 5.8, 5.9)	(6, 6.2, 6.6)
5	1	(3.8, 4, 4.2)	(4.3, 4.5, 4.6)	(4.65, 4.8, 5)
	2	(3.5, 4, 4.2)	(4.4, 4.5, 4.7)	(4.8, 5, 5.6)
	3	(9, 10, 10.5)	(10.8, 11, 11.2)	(11.3, 11.5, 11.6)

FIGURE 1: Relationship between quality and cost.

quality 700 and the minimum cost 6871.17, and the corresponding optimal solution is reported in Table 6. Table 6 shows the optimal supplier-level assignment mode and the order amounts of each product procured from its primary suppliers. For example, the primary suppliers for product 1 are the second, fourth, and fifth suppliers, and its level-2 and level-3 suppliers are the first one and the third one, respectively. The order amounts from primary suppliers for product 1 are 76.5, 75.5, and 36.8 units.

The biobjective supplier selection model is solved several times through varying the target values G_1 and G_2 in order to obtain a suitable solution such that the decision maker can realize the trade-off of one criterion against another one. By computation, the relationship between quality and cost is shown in Figure 1. According to Figure 1, we can find
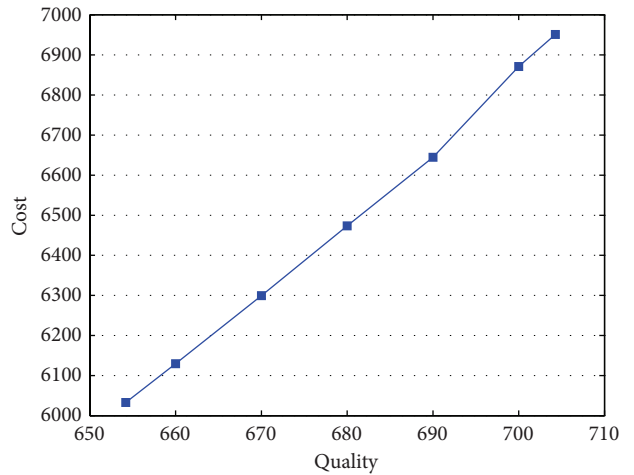
that increasing value of the first objective causes that of the second objective to increase. Also, decreasing value of the first objective causes that of the second objective to decrease. Therefore, it seems that, by raising the target value for any of the objectives, we can create more space for another objective to be improved. It is also concluded that there exist some positive correlations between the quality and the total cost.

In order to identify the impact of model parameters on solution quality, we try to look for the optimal solutions by adjusting independently the values of parameters α_{sp} and β_p. The computational results are reported in Table 7, where the symbol $(\mathrm{obj}_1, \mathrm{obj}_2)$ represents the objective function values of corresponding optimal solution. From Table 7, we can find that the quality objective function value equals its target value 700, while the total cost objective function value has a gap with its target value 6000. On the one hand, the total cost increases gradually with respect to the increasing values of

Table 5: Capacity data for supplier selection problem.

Product	Capacity				
	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5
1	(42, 50, 60)	(75, 90, 100)	(60, 70, 80)	(75, 80, 90)	(60, 75, 80)
2	(40, 45, 56)	(80, 100, 115)	(45, 50, 54)	(180, 200, 250)	(85, 100, 125)
3	(80, 100, 110)	(16, 20, 30)	(120, 150, 170)	(40, 50, 65)	(60, 75, 85)

Table 6: Solution result for biobjective supplier selection model.

Supplier	Product	Supplier-level assignment			Order amount		
		Level-1	Level-2	Level-3	Level-1	Level-2	Level-3
1	1	0	1	0	0	0	0
	2	0	1	0	0	0	0
	3	1	0	0	82	0	0
2	1	1	0	0	76.5	0	0
	2	1	0	0	82	0	0
	3	0	1	0	0	0	0
3	1	0	0	1	0	0	0
	2	0	0	1	0	0	0
	3	1	0	0	100.63	0	0
4	1	1	0	0	75.5	0	0
	2	1	0	0	145.23	0	0
	3	0	0	1	0	0	0
5	1	1	0	0	36.8	0	0
	2	1	0	0	86.5	0	0
	3	1	0	0	61.5	0	0

Table 7: Parameters analysis about α_{sp} and β_p for biobjective supplier selection model.

α_{sp}	The optimal values (obj$_1$, obj$_2$)					
	$\beta_p = 0.98$	$\beta_p = 0.9$	$\beta_p = 0.85$	$\beta_p = 0.8$	$\beta_p = 0.75$	$\beta_p = 0.7$
0.95	(700, 6859.32)	(700, 6839.59)	(700, 6819.84)	(700, 6800.10)	(700, 6784.85)	(700, 6778.12)
0.9	(700, 6806.81)	(700, 6775.22)	(700, 6755.48)	(700, 6741.49)	(700, 6734.76)	(700, 6728.02)
0.7	(700, 6565.37)	(700, 6554.59)	(700, 6547.85)	(700, 6541.12)	(700, 6534.37)	(700, 6527.27)

β_p for the same parameter α_{sp}. On the other hand, the total cost decreases gradually with respect to the decreasing values of α_{sp} for the same parameter β_p.

Lead time in supply chain management is a crucial parameter. To highlight the role of lead time in supplier selection planning, we perform some experiments to measure its effect. In this case, we report the computational results in Table 8. Table 8 shows that there is much difference in terms of the optimal decision and corresponding objective value when the parameter L changes. Furthermore, if the acceptable lead time turns small, the total cost has the increasing trend. So it is concluded that there exist some negative correlations between the total cost and the lead time.

6. Conclusions

In the present study, the fuzzy supplier selection problem is considered, including biobjective model, property analysis, solution method, and numerical experiments. The innovation results of the paper are summarized as follows.

(i) A biobjective fuzzy supplier selection model with uncertain variable cost, supplier capacity, and buyer demand is built, in which maximizing the total product quality and minimizing the total cost are our two objectives.

(ii) The basic properties of presented model are discussed (Theorems 1, 2, and 3). From the theoretical results, we obtain the analytical expressions of the expected value objective and credibility constraints which transform the original fuzzy model into its equivalent deterministic one.

(iii) A solution procedure integrated with the preemptive goal programming is designed, which transforms our model into a crisp single objective version. This transformation reduces computational complexity

TABLE 8: Parameters analysis about L for biobjective supplier selection model.

L	Product	Level			Order amounts	$(\text{obj}_1, \text{obj}_2)$
		1	2	3		
2700	1	(s_2, s_4, s_5)	s_1	s_3	(76.5, 75.5, 35)	
	2	(s_2, s_4, s_5)	s_1	s_3	(82, 131.53, 86.5)	(681, 6725.43)
	3	(s_1, s_3, s_5)	s_2	s_4	(82, 95.5, 61.5)	
2800	1	(s_2, s_4, s_5)	s_1	s_3	(76.5, 75.5, 36.8)	
	2	(s_2, s_4, s_5)	s_1	s_3	(82, 145.23, 86.5)	(700, 6871.17)
	3	(s_1, s_3, s_5)	s_2	s_4	(82, 100.63, 61.5)	
2900	1	(s_2, s_4, s_5)	s_1	s_3	(59.37, 75.5, 52.13)	
	2	(s_2, s_4, s_5)	s_1	s_3	(82, 154.93, 86.5)	(700, 6644.16)
	3	(s_1, s_3, s_5)	s_2	s_4	(82, 123, 34)	
3000	1	(s_2, s_4, s_5)	s_1	s_3	(56.52, 75.5, 54.98)	
	2	(s_2, s_4, s_5)	s_1	s_3	(82, 150.79, 86.5)	(700, 6470.64)
	3	(s_1, s_3, s_4)	s_5	s_2	(82, 123, 41)	
3100	1	(s_3, s_4, s_5)	s_1	s_2	(52.49, 73, 61.5)	
	2	(s_2, s_4, s_5)	s_1	s_3	(82, 158.06, 86.5)	(700, 6400.62)
	3	(s_1, s_3, s_5)	s_2	s_4	(82, 123, 34)	

and makes the application of our procedure more understandable.

(iv) A numerical example is performed to verify the effectiveness of the proposed model for illustration purpose. The computational results verify that our solution method works well and provides acceptable solution, which hopefully can help decision maker in management.

Notations

S: Set of suppliers considered, indexed by s, $s = 1, 2, \ldots, n$

P: Set of products, indexed by p, $p = 1, 2, \ldots, |P|$

R: Set of levels, indexed by r, $r = 1, 2, \ldots, n - m + 1$

F_{rsp}: The fixed cost that supplier s charges for product p as level-r supplier

Q_{sp}: The quality level of unit product p from its supplier s

L_{rsp}: The lead time for unit product p from its level-r supplier s

L: The maximal lead time

ξ_{rsp}: The fuzzy cost for unit product p from its level-r supplier s

η_{sp}: The fuzzy capacity at supplier s for product p

ζ_p: The fuzzy demand for product p

x_{rsp}: A binary variable indicating whether supplier s is assigned as a level-r supplier for product p or not

y_{1sp}: The order of product p distributed from its primary supplier s.

Conflict of Interests

The author declares that there is no conflict of interests regarding the publication of this paper.

Acknowledgment

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