ارائه شده توسط:

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A fuzzy multi-objective model for provider selection in data communication services with different QoS levels

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1. Introduction

With the development of e-commerce, data communication service is particularly important today because of the tremendous impact on the profits of purchase company. In data communication domain, one of the most challenging issues is provider selection. In some firms, purchased materials and services sometimes represent up to eighty percent of total product cost (Ghobadian et al., 1993).

Quality of service (QoS) is the collective summation of service measures, which determines the degree of user satisfaction of the service (Ahsan, 2006). Common measures of QoS are delay, reliability and missing data probability in data communication networks. Delay specifies how long it takes for data to travel across the network from source to destination (Comer, 2001).

Reliability represents the variance in data transmission. Audio and video applications are quite sensitive to delay and reliability, whereas common data services are insensitive to either (Ragsdale et al., 2000). Missing data represents information dropped or irrecoverably damaged by the network. It typically stems from data collision and buffer overflows. Sudden changes in transmission may also cause data loss (Teitelbaum and Sadagic, 2002). In some important tasks, missing data sometimes leads to incomplete information in data transmission.

In general, a firm has two options when the transmitted data is lost. It can (1) ignore the lost frames or (2) send a re-transmission request to the sender. Ignoring lost frames is appropriate for unimportant tasks or real-time (time-fixed) applications such as video conference, as they are sensitive to timeliness of data. However, some data applications require re-transmission. For example, some file transfer tasks require submitting all data.

Meanwhile, missing data usually causes loss to customers. To address this issue, a penalty function is created to reflect the importance of a task. The more important the task, the higher the penalty for not achieving the desired targets. Based on this relationship, we can define the penalty function in different tasks. A decision maker should therefore consider both the magnitude of the penalty and the unit cost of the provider when assigning tasks to providers.

Moreover, when consumers decide which provider to select, they expect not only low costs, but also high QoS levels such as lower delay and higher reliability. Thus, the provider selection becomes a multi-criteria decision making problem involving several conflicting factors. Consequently a manager must analyze the tradeoff among several criteria such as price, delay and reliability.

For example, in the last decade, wireless mobile data services have grown at an impressive rate. Especially, China now has the largest mobile communication network in the world in December 2006. The number of mobile communication subscribers in China reached 461.082 million, and the ownership of mobile phones was 0.353. Meanwhile, with the development of this market, more and more wireless mobile data service providers had occurred in...
China, such as China Mobile Communication Corporation, China United Telecommunications Corporation and so on. In this situation, many companies consider not only service price but also QoS level when they purchase wireless mobile data service for improving competition ability.

Current research has devised techniques in order to help consumers in the provider selection process. For example, Armony and Haviv (2003) studied provider selection problems in which two firms offered identical services for possibly different prices and response times. Kasap et al. (2007) investigated an optimization problem a firm faces when acquiring network capacity from multiple providers. Raghuram and Munindar (2004) reformulated two traditionally recommended approaches for service selection and proposed a new agent-based approach in which agents cooperate to evaluate service providers.

Due to the uncertainties associated with the costs and the QoS in acquiring data, the value of many criteria and constraints has been expressed in vague terms such as ‘very high in quality’ or ‘low in price’. In this situation, the theory of fuzzy sets is the best tool for handling uncertainty. Fuzzy set theory is employed due to the presence of vagueness and imprecision of information in the provider selection problem.

Based on fuzzy logic approaches, Kumara et al. (2006) proposed fuzzy goal programming for a supplier selection problem with multiple sources that included three primary goals: minimizing the net cost, minimizing the net rejections, and minimizing the net late deliveries subject to realistic constraints regarding the buyer’s demands and the vendor’s capacity. In this proposed model, Zimmermann’s weightless technique is used in which there is no difference between objective functions.

Wang et al. (2008) provided a new decision model under vague information for selection of web services. Wang et al. (2007) proposed a fuzzy model with QoS support. Unlike similar research, Wang proposed a method which considered not only the objective factors described by service providers, but also the subjective information with trustable evaluations from users who use those services. Amida et al. (2006) provided a fuzzy multi-objective supplier selection, where the objective of the model is fuzzy when constraints and weights are deterministic.

It is common for providers to offer a price break to encourage the larger buyers to purchase their services. For example, Amida et al. (2009) constructed a fuzzy weighted additive and mixed integer linear program. The multi-objective model determines the order quantities to each supplier based on price breaks. Pan et al. (2008) developed a fuzzy order allocation program. This model considers the imprecision of information and price break when constraints and weights are deterministic.

But these multi-objective models commonly do not simulta-

neously consider information uncertainty, the general objective membership function, different penalty functions and multiple class services together for selecting the most suitable provider of data communication service. In order to provide a more practical and meaningful solution to the provider selection problem, we present a new fuzzy multi-objective model in this paper, which reflects both subjective judgment and objective information in real-life circumstances. The proposed method in our research incorporates the concepts of stochastic theory, fuzzy sets and scenario analysis to conduct the selection of provider. Therefore, this method will efficiently manage the vagueness and ambiguity existing in the available information as well as the essential fuzziness in human judgment and preference.

This paper differs from past studies in that it includes the following four features:

(1) Uncertain information includes weight, objectives, constraints and customer demand.

(2) Unit price is aligned with order quantity change.

(3) Providers offer different QoS levels to customers.

(4) Different penalty functions are defined in scenario analysis.

(5) The objective membership functions consist of both linear and non-linear functions.

In the following contents, we assume that a market includes a great number of service consumers (when they request a service) and many service providers (when they offer to provide a service implementation). For simplicity, we assume that each provider offers the service with different QoS levels to a consumer.

Now the main problem is how to select a suitable provider when considering price breaks, non-linear objective membership function, different penalty functions and multiple QoS levels together for a consumer in a fuzzy environment.

The rest of this paper is organized as follows. In Section 2, we present a new provider selection model. The model includes multiple QoS levels, different penalty functions, price breaks, etc. In Section 3, we develop this new provider selection model in a fuzzy environment. In this model, not only the objectives, weights and constraints are fuzzy and demand is stochastic, but also the objective membership function is non-linear. In Section 4, we propose a valid decision making process for this model. In Section 5, we develop algorithms for this model. In Section 6, we present a numerical example. From data analysis, we obtain some useful results to support the provider selection decision. Finally, the concluding remarks are presented in Section 7.

2. A multi-objective model for provider selection in data communication services with different QoS levels

The user receives demand information from customers and allocates the corresponding service order in multiple provider environments. The problem here is, when the user makes an order to purchase a service, how to allocate an order in its list of providers. Notably, provider selection is a multiple criteria decision-making problem, the multi-objective decision model needs to be built to allocate the order among multiple providers.

Meanwhile, in the existing related models concentrating on provider selection, researchers rarely have simultaneously considered stochastic demand, multiple QoS levels, different penalty functions, and price breaks. Our model recognizes that this phenomenon must be considered in order to solve such a provider selection problem. The following content discusses our model in detail. We first make the following assumptions:

(1) Demand is stochastic.

(2) Provider capacities are limited.

(3) Unit price varies with quantity.

(4) Providers offer different QoS levels to meet customer demand.

(5) Penalty function definition is only influenced by scenario.

(6) The objective membership function is non-linear.

Moreover, we use the following notations throughout this paper.

\[ D \] Demand over the selling period

\[ q \] The number of objectives

\[ d \] The number of negative objectives

\[ e \] The number of positive objectives

\[ m \] Number of constraints

\[ n \] Number of providers

\[ m_t \] Price level of the \( t \)th provider, \( t = 1, 2, \ldots, n \)

\[ p_{tj} \] Price of the \( t \)th provider at \( j \)th price level, \( j = 1, 2, \ldots, m_t \)
\( V_t \) Maximum demand quantity from the \( t \)th provider at \( j \)th price level

\( C_t \) Maximum capacity from the \( t \)th provider

\( V^*_t \) A constant variable, slightly larger than \( V_t \)

\( x_{ij} \) Transmission data quantity of user from the \( t \)th provider at the \( j \)th price level, \( x_{ij} \in x, \) where \( x = \{x_{11}, x_{12}, \ldots, x_{nm} \} \)

\( y_t \) The decision variable determines if the \( t \)th provider at the \( j \)th price is selected or not, where \( y_{ij} = 1 \), if the \( t \)th provider is selected at the \( j \)th price level; otherwise \( y_{ij} = 0 \)

\( \theta_t \) Missing rate of transmission data for the \( t \)th provider at the \( j \)th price level

\( F(x_t) \) Penalty function of \( x_t \)

\( L_{ij} \) Percentage of items that suffers delay in delivery for the \( t \)th provider at the \( j \)th price level

\( R_t \) Percentage of reliable units for the \( t \)th provider at the \( j \)th price level

\( \alpha \) A parameter for the \( p \)th objective membership function, \( \alpha_p > 0 \)

\( \epsilon \) A coefficient for linear penalty function, \( \epsilon > 0 \)

\( \nu, \gamma \) Coefficients for nonlinear penalty function, \( \nu \) and \( \gamma \) are respectively exponential parameter and product parameter, \( \nu > 1, \gamma > 0 \)

\( f \) Objective function \( f = \{f_1, f_2, \ldots, f_q \} \)

Then, a new general multi-objective model can be stated as follows:

\[
\begin{align*}
\text{min} f_d &= \{f_1, f_2, \ldots, f_h\}, \\
\text{max} f_e &= \{f_{h+1}, f_{h+2}, \ldots, f_{q-h}\},
\end{align*}
\]

with the following constraint:

\[
\begin{align*}
g_i &= \left\{ \left( \sum_{t=1}^{n} \sum_{j=1}^{m} a_{ij} x_{ij} \geq b_i \right) \right\} \geq \beta_i, \quad (2.3)
\end{align*}
\]

where \( f_1, f_2, \ldots, f_h \) are the negative objectives or criteria-like costs, delay, etc., \( i = 1, 2, \ldots, m, f_{h+1}, f_{h+2}, \ldots, f_{q-h} \) are the positive objectives or criteria such as reliability, bandwidth and so on. \( b_i \) is the \( i \)th independent continuous random variable with given distributions, while \( a_{ij} \) represents the coefficient of the \( t \)th decision variable in the \( i \)th constraint. \( \beta_i \) is the \( i \)th pre-assigned probability level and \( P(\cdot) \) represents the probability.

However, to have a new specific multi-objective model for the provider selection problem, we assume that the criteria include cost \( f_1 \), reliability \( f_2 \) and delay \( f_3 \) together with a major constraint in selecting a service that can satisfy a demand. Each provider has its own unit cost, delay history and reliability record. A user orders the required service from providers in its provider list.

We let \( d_t \) and \( \beta \) respectively represent the coefficient of the \( t \)st decision variable and the pre-assigned probability level in the demand constraint. Meanwhile, the \( t \)th provider can provide up to \( C_t \) units of the service over the planning period, i.e., \( \sum_{j=1}^{m} x_{ij} \leq C_t \). This is due to service capacity. Then, we have that

\[
\begin{align*}
P\left( \sum_{t=1}^{m} \sum_{j=1}^{m} d_{ij} y_{ij} x_{ij} \geq D \right) \geq \beta.
\end{align*}
\]

Since information dropped or irrecoverably damaged in data communication service is unavoidable, a penalty function should be considered and defined. Notably, missing data usually causes loss to customers. Moreover, the more important the task is, the higher the penalty will be for not achieving desired targets. According to this relationship, we assume that scenarios are divided into three conditions and accordingly three different penalty functions are defined as follows:

(1) When the missing data \( x_{ij} \) is unimportant, the penalty function is equal to zero, i.e.,

\[
F(x_{ij}) = 0.
\]

(2) When the missing data \( x_{ij} \) is common, the penalty function is linear as follows:

\[
F(x_{ij}) = \theta_p x_{ij}.
\]

(3) When the missing data \( x_{ij} \) is important, the penalty function is nonlinear as follows:

\[
F(x_{ij}) = \theta_p x_{ij}^e.\]

The objective function for cost can be stated as follows:

\[
f_1 = \sum_{t=1}^{n} \sum_{j=1}^{m} \left[ \theta_p x_{ij} + F(x_{ij}) \right],
\]

which should minimize the cost of service.

The objective function for reliability is defined as

\[
f_2 = \sum_{t=1}^{n} \sum_{j=1}^{m} R_t x_{ij},
\]

which should maximize the number of reliable units.

The aggregate performance measure for delivery delay objective function is defined as

\[
f_3 = \sum_{t=1}^{n} \sum_{j=1}^{m} L_t x_{ij},
\]

which should minimize the number of delayed services.

We let \( f_1^*, f_2^* \) and \( f_3^* \) represent the minimal cost, the maximal reliability and the minimal delivery delay, respectively. Then we have the final form of the integer multi-objective model for purchasing data communication services in multiple source networks is as follows:

\[
\begin{align*}
f_1^* &= \min \left\{ \sum_{t=1}^{n} \sum_{j=1}^{m} \left[ \theta_p x_{ij} + F(x_{ij}) \right] \right\}, \quad \text{(cost)}
\end{align*}
\]

\[
\begin{align*}
f_2^* &= \max \left\{ \sum_{t=1}^{n} \sum_{j=1}^{m} R_t x_{ij} \right\}, \quad \text{(reliability)}
\end{align*}
\]

\[
\begin{align*}
f_3^* &= \min \left\{ \sum_{t=1}^{n} \sum_{j=1}^{m} L_t x_{ij} \right\}, \quad \text{(delay)}
\end{align*}
\]

Generally, users do not have exact and complete information related to decision criteria and constraints. For provider selection problems, the collected data does not behave crisply, some are typically fuzzy, and others are stochastic in nature.

Our multi-objective model is developed to deal with these problems. In the new multi-objective provider selection model presented in this paper, we let sign " ~ " indicate the fuzzy
environment, symbol \( "s" \) in the objectives and constraints indicate fuzziness of \( "r" \), i.e., approximately greater than or equal to. In contrast, \( "s" \) has a linguistic interpretation “essentially smaller than or equal to”. The following section discusses our model in a fuzzy environment.

3. A fuzzy multi-objective provider selection model

Here we present a new fuzzy multi-objective provider selection model that can be expressed as follows:

\[
f(d) \leq f(e), \quad d = 1, 2, \ldots, h, \tag{3.1}\]

\[
f(e) \geq f(f), \quad e = 1, 2, \ldots, q - h, \tag{3.2}\]

The decision-maker is almost satisfied if

\[
P \left( \sum_{i=1}^{n} \sum_{j=1}^{m} a_{ij} y_{ij} \geq b_{i} \right) \geq \beta_{i}, \quad i = 1, 2, \ldots, m, \tag{3.3}\]

\[
\sum_{i=1}^{n} y_{ij} = 1, \quad \text{or} \quad \sum_{i=1}^{n} y_{ij} > 1, \quad \text{or} \quad \sum_{i=1}^{n} y_{ij} \geq 1, \tag{3.4}\]

\[
V_{ij}^{*} = V_{ij} + 1, \tag{3.5}\]

\[
y_{ij} \in [0, 1], \tag{3.6}\]

\[
\sum_{j=1}^{m} x_{ij} \leq c_{i}, \quad \forall x_{ij} \geq 0, \tag{3.8}\]

where \( a_{ij} \), \( b_{i} \), and \( \beta_{i} \) respectively are the coefficient of the \( t \)th decision variable in the \( i \)th constraint, the \( i \)th independent continuous random variable with given distributions, and the \( i \)th pre-assigned probability level defined in Section 3.

By considering \( c_{i} \) and \( \delta_{i} \), where \( c_{i} > 0 \) and \( 0 < \delta_{i} < \beta_{i} \), \( i = 1, 2, \ldots, m \) as the decision-maker’s predetermined values, the satisfaction constraints of the decision-maker can be stated as follows.

The decision-maker is fully satisfied if

\[
P \left( \sum_{i=1}^{n} \sum_{j=1}^{m} a_{ij} y_{ij} \geq b_{i} \right) \geq \beta_{i}, \tag{3.9}\]

The decision-maker is almost satisfied if

\[
\delta_{i} < P \left( \sum_{i=1}^{n} \sum_{j=1}^{m} a_{ij} y_{ij} \geq b_{i} \right) < \beta_{i}, \tag{3.10}\]

or

\[
P \left( \sum_{i=1}^{n} \sum_{j=1}^{m} (a_{ij} + c_{ij}) y_{ij} \geq b_{i} \right) \geq \beta_{i}. \tag{3.11}\]

Then, the equivalent deterministic constraints for Eqs. (3.9)–(3.11) are

\[
\sum_{i=1}^{n} \sum_{j=1}^{m} a_{ij} y_{ij} \geq F_{i}^{-1}(\beta_{i}). \tag{3.12}\]

Finally, to obtain Eqs. (3.16) and (3.17), it is necessary to build membership functions \( \mu_{f} \) and \( \mu_{g} \) by the corresponding \( f_{p} \) and \( g_{i} \). For maximizing objective functions, we use the following membership functions:

\[
\mu_{f}(x) = \begin{cases} 
1, & f_{p} \geq \max f_{p} \\
\frac{f_{p} - \min f_{p}}{\max f_{p} - \min f_{p}}, & \min f_{p} < f_{p} < \max f_{p} \\
0, & f_{p} \leq \min f_{p} \end{cases}, \tag{3.18}\]

\[
\mu_{g}(x) = \begin{cases} 
1, & f_{p} \leq \min f_{p} \\
\frac{\max f_{p} - f_{p}}{\max f_{p} - \min f_{p}}, & \min f_{p} < f_{p} < \max f_{p} \\
0, & f_{p} \geq \max f_{p} \end{cases}. \tag{3.19}\]

The construction of Eq. (3.18) or (3.19) aims to solve the following problems:

\[
f_{p} \rightarrow \min f_{p}, \tag{3.20}\]

\[
f_{p} \rightarrow \max f_{p} \tag{3.21}\]

where \( \min f_{p} \) and \( \max f_{p} \) are obtained through solving the multi-objective problem as a single objective.

Fig. 1 shows the different membership functions of the objective.

Since the value of every objective function \( f_{p} \) changes from \( \min f_{p} \) to \( \max f_{p} \), \( f_{p} \) may be considered as a fuzzy number with the
The fuzzy solution for all fuzzy objectives and fuzzy constraints may be given as follows:

$$\mu_D = \left\{ \bigcap_{i=1}^{m} \mu_{f_j}, \bigcap_{p=1}^{q} \mu_{g_k} \right\}$$

where $\mu_{f_j}, \mu_{g_k}$ are defined in Section 4, $q$ is the number of objectives, and $m$ is the number of constraints.

The optimal solution $\mu^*_D$ for all fuzzy objectives and fuzzy constraints is given as follows:

$$\mu^*_D = \max(\mu_D)$$

In a real situation, the confluence of different objectives and constraints has unequal importance to the decision maker. The fuzzy weighted additive model can handle this problem, which is described in the next paragraph. The weighted additive model is widely used in vector-objective optimization problems.

The basic concept is to use a single utility function to express the overall preference of the decision maker and the relative importance of the criteria (Lia et al., 2006; Hwang and Masud, 1979). In this case, multiplying each membership function of fuzzy goals by their corresponding weights and then adding the results together produces a linear weighted utility function.

Let $w_k$ denote the fuzzy weight of the $k$th objective or constraint, where $k = 1, 2, \ldots, q + m$. Then the fuzzy model proposed by Bellman and Zadeh, Sakawa and the weighted additive model (Zadeh, 1975; Sakawa, 1993; Tiwari et al., 1987) is shown below:

$$\mu_D = \sum_{k=1}^{q} w_k \eta + \sum_{k=q+1}^{q+m} w_k \kappa,$$

$$\sum_{p=1}^{q} w_p \eta + \sum_{i=1}^{m} w_{g_i} \geq 1, \quad w_p, w_{g_i} \geq 0$$

where $w_p$ and $w_{g_i}$ are the weighting coefficients that present the relative importance among the fuzzy goals and the fuzzy constraints, respectively. $\eta$ and $\kappa$ are the fuzzy goal and the fuzzy constraint, respectively.

Zadeh (1975) studied the concept of a linguistic variable and its application to approximate reasoning. The concept of a linguistic variable provides a means of approximate characterization of phenomena which are too complex or too ill-defined to be amenable to description in conventional quantitative terms. Sakawa (1993) firstly provided integrative ambiguous parameters in problem formulation with fuzzy goals for multi-objective optimization into a unified methodology. Tiwari et al. (1987) formulated an additive model to solve Fuzzy Goal Programming (FGP). The method used arithmetic addition to aggregate the fuzzy goals to construct the relevant decision function. Cardinal and ordinal weights for nonequivalent fuzzy goals were also incorporated in the method. By applying Zadeh (1975), Sakawa (1993) and Tiwari et al. (1987), we present a new fuzzy multi-objective provider selection model as follows:

$$\max(\bar{w}_f \eta + \bar{w}_g \kappa),$$

$$\eta \leq \mu_f,$$

$$\kappa \leq \mu_g$$

where $\bar{w}_f$ and $\bar{w}_g$ are the fuzzy weighting coefficients that present the relative importance among the fuzzy goals and the fuzzy constraints, respectively.

Let $\bar{w}_f = (\bar{w}_{f_1}, \bar{w}_{f_2}, \bar{w}_{f_3})$ be a trapezoidal fuzzy number, and let $\bar{w}_g = (\bar{w}_{g_0}, \bar{w}_{g_1}, \bar{w}_{g_2})$ be a triangular fuzzy number, where $\bar{w}_{f_0}$ and $\bar{w}_{g_0}$ are the minimal value and the maximal value, respectively.

It is noticed that, $\bar{w}_f$ is a decision variable, in addition to $\eta, \kappa, x_q$ and $y_f$. The crisp constraint set equation (4.11) is derived by applying...
the $\alpha$-cut approach (Rough approximations Alpha-Approach) to the trapezoidal membership functions of the fuzzy weights, where $\alpha$ is a predetermined value $\alpha \in (0, 1]$. Constraint equation (4.12) insures that the relative weights should add up to 1.

Then, by utilizing the $\alpha$-cut approach for $w_k$, as a trapezoidal fuzzy number, the suggested model can be represented in the form of a weighted max-min deterministic-crisp linear programming model as follows:

$$
\text{max } \left\{ \sum_{k=1}^{n+m} w_k \eta_k + \sum_{k=q+1}^{n+m} w_k \eta_k \right\},
$$

subject to

$$
\eta_k \leq \mu_{\xi_k},
$$

(4.8)

$$
k_i \leq \mu_{\xi_i},
$$

(4.9)

$$
w_k(1-\alpha) + w_{k1} \leq w_k \leq w_k(1-\alpha) + w_{k2},
$$

(4.10)

$$
\sum_{k=1}^{n+m} w_k = \sum_{p=1}^{q} w_{f_p} + \sum_{i=1}^{m} w_{k_i} = 1, \quad w_{f_p}, w_{k_i} \geq 0,
$$

(4.11)

$$
\sum_{i=j}^{m} y_{ij} = 1, \quad \text{or} \quad \sum_{i=j}^{m} y_{ij} > 1, \quad \text{or} \quad \sum_{i=j}^{m} y_{ij} \leq 1,
$$

(4.12)

$$
\eta_{y} = \eta_{v} + 1,
$$

(4.13)

$$
y_{ij} y_{y} = x_{ij} \leq y_{ij} v_{ij},
$$

(4.14)

$$
x_{ij} \geq 0, \quad \sum_{j=1}^{m} x_{ij} \leq C_{i},
$$

(4.15)

$$
\sum_{j=1}^{m} y_{ij} \leq 1, \quad y_{ij} \in [0, 1] \quad \text{for all } i, j.
$$

(4.16)

(4.17)

The decision-maker has to set the value of $\alpha$, carefully, to avoid infeasible solutions. Also, the fuzzy weights reflect the uncertain relative importance of the objectives, where the values of all fuzzy weights should satisfy $\sum_{k=1}^{n+m} w_k = 1$.

On the other hand, if $w_k$, for any $k$th objective or constraint, is considered as a triangular fuzzy number, then $w_k$ and $w_{k2}$ should be replaced by $w_{k0}$, for the $k$th objective or constraint.

5. An algorithm

Because we considered fuzzy goals, fuzzy weights and fuzzy (stochastic) constraints in our model, a major difficulty is the uncertainty of data. To solve this problem, we need to combine features of fuzzy data and stochastic data, for example, the membership function, the distribution of random variables and so on. As mentioned above, in this section, we construct an efficient implementation of the fuzzy multi-objective algorithm. The original algorithm was not only usually linear, but also cannot simultaneously deal with fuzzy data and stochastic data. However, in practice model includes linear and nonlinear. Meanwhile, fuzzy and stochastic data was general. To solve these problems, we reconstructed the new algorithm, it could overcome those weak points. Our new algorithm was stated with 8 steps as follows:

(1) Construct provider selection model according to the criteria and the constraints of the client and provider.

(2) Let the objective membership function be constructed according to Eq. (3.18) (respectively (3.19)). Find every maximized objective value (respectively minimized objective value).

(3) Let the membership function be constructed according to Eq. (3.22). Define the probabilistic fuzzy goal constraint.

(4) According to the actual situation, give the distribution of random variables $b_i$ and the fuzzy number of weights.

(5) Construct an initial vector $b_0$ and $w_0$ of the important factors.

(6) Using the membership function, construct the multi-objective stochastic fuzzy model according to Eqs. (4.5)-(4.7).

(7) Establish the equivalent crisp model of the fuzzy optimization problem according to Eqs. (4.8)-(4.17).

(8) Find the optimal solution vector $x^*$ by Eqs. (4.8)-(4.17), where $x^*$ is the efficient solution of the multi-objective provider selection model with the fuzzy weights in different $\alpha$.

The algorithm of the model is illustrated by a numerical example in the next section.

6. A numerical example

In this section, we present a numerical example to illustrate the proposed method presented in this paper and show that the method is an effective method for determining service selection from multiple providers. We first make the following assumptions:

(1) The prices are divided into 3 levels for each provider.

(2) Demand is a normally distributed random variable with mean 30, variance 25 and the maximal value 45. Three provider capacities are limited.

(3) Objectives include cost $f_1$, reliability $f_2$ and delay $f_3$. Data is provided in Table 1. The only constraint is that supply must almost satisfy demand.

(4) The decision makers’ relative weights of the fuzzy goals and constraints are shown in Table 2. Moreover, $\delta_t = 1$, $\epsilon = \gamma = \lambda_p = 1$, $W = 0.8$, $\nu = 2$, $\alpha = 0.1$.

This example consists of three fuzzy objectives as follows:

Case 1: Without penalty function, the values for the decision variables in the numerical example are shown in Table 4:

$$
F(x) = 0,
$$

$$
\begin{align*}
\text{Case 1: Without penalty function, the values for the decision variables in the numerical example are shown in Table 4:} \\
& F(x) = 0, \\
& f_1 = 3x_{11}y_{11} + 2.6x_{12}y_{12} + 2.4x_{13}y_{13} + 3.5x_{21}y_{21} + 2.8x_{22}y_{22} \\
& 4.2x_{23}y_{23} + 2.8x_{31}y_{31} + 2.5x_{32}y_{32} + 2.2x_{33}y_{33}.
\end{align*}
$$

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Collected data for numerical example.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Provider</td>
<td>Quantity</td>
</tr>
<tr>
<td>1</td>
<td>0≤x_{11}≤16</td>
</tr>
<tr>
<td>2</td>
<td>0≤x_{12}≤16</td>
</tr>
<tr>
<td>3</td>
<td>33≤x_{13}≤32</td>
</tr>
<tr>
<td>1</td>
<td>0≤x_{21}≤16</td>
</tr>
<tr>
<td>2</td>
<td>0≤x_{22}≤32</td>
</tr>
<tr>
<td>3</td>
<td>33≤x_{23}≤32</td>
</tr>
<tr>
<td>1</td>
<td>0≤x_{31}≤16</td>
</tr>
<tr>
<td>2</td>
<td>17≤x_{32}≤32</td>
</tr>
<tr>
<td>3</td>
<td>33≤x_{33}≤32</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Weight value.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\psi_1$</td>
<td>0.4</td>
</tr>
<tr>
<td>$w_2$</td>
<td>0.4</td>
</tr>
<tr>
<td>$w_3$</td>
<td>0.3</td>
</tr>
<tr>
<td>$w_4$</td>
<td>0.3</td>
</tr>
</tbody>
</table>
**Table 3**
The lower and upper bounds value of the objective functions under different customer preferences.

<table>
<thead>
<tr>
<th>Objective</th>
<th>$y_{i1}$</th>
<th>$y_{i2}$</th>
<th>$\mu = 0$</th>
<th>$\mu = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$ (no penalty)</td>
<td>$\frac{1}{3} \sum_{i=1}^{3} y_{i1} = 1$</td>
<td>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</td>
<td>72.6</td>
<td>140.4</td>
</tr>
<tr>
<td>$f_1$ (linear loss)</td>
<td>$\frac{1}{3} \sum_{i=1}^{3} y_{i1} = 1$</td>
<td>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</td>
<td>75</td>
<td>149.5</td>
</tr>
<tr>
<td>$f_1$ (nonlinear loss)</td>
<td>$\frac{1}{3} \sum_{i=1}^{3} y_{i1} = 1$</td>
<td>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</td>
<td>136.88</td>
<td>282.99</td>
</tr>
</tbody>
</table>

**Table 4**
Decision variable values without penalty function under different customer preferences.

<table>
<thead>
<tr>
<th>No penalty</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i1} = 1$</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_{11}$</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{13}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{21}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{22}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{23}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{24}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{31}$</td>
<td>33</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{32}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{33}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$w_1$</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>$w_2$</td>
<td>0.46</td>
<td>0.41</td>
<td>0.41</td>
</tr>
<tr>
<td>$w_3$</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>$w_4$</td>
<td>0.31</td>
<td>0.36</td>
<td>0.36</td>
</tr>
<tr>
<td>Objective</td>
<td>0.721</td>
<td>0.899</td>
<td>0.892</td>
</tr>
</tbody>
</table>

**Table 5**
Decision variable values with linear penalty function under different customer preferences.

<table>
<thead>
<tr>
<th>Linear penalty</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i1} = 1$</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_{11}$</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{13}$</td>
<td>0</td>
<td>33</td>
<td>0</td>
</tr>
<tr>
<td>$x_{21}$</td>
<td>0</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>$x_{22}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{23}$</td>
<td>0</td>
<td>0</td>
<td>44</td>
</tr>
<tr>
<td>$x_{31}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{32}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{33}$</td>
<td>33</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$w_1$</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>$w_2$</td>
<td>0.46</td>
<td>0.41</td>
<td>0.41</td>
</tr>
<tr>
<td>$w_3$</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>$w_4$</td>
<td>0.31</td>
<td>0.36</td>
<td>0.36</td>
</tr>
<tr>
<td>Objective</td>
<td>0.721</td>
<td>0.755</td>
<td>0.805</td>
</tr>
</tbody>
</table>

**Table 6**
Decision variable values with non-linear penalty function under different customer preferences.

<table>
<thead>
<tr>
<th>Non-linear penalty</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i1} = 1$</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</th>
<th>$\frac{1}{3} \sum_{i=1}^{3} y_{i2} &gt; 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_{11}$</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{13}$</td>
<td>0</td>
<td>33</td>
<td>0</td>
</tr>
<tr>
<td>$x_{21}$</td>
<td>0</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>$x_{22}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{23}$</td>
<td>0</td>
<td>0</td>
<td>44</td>
</tr>
<tr>
<td>$x_{31}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{32}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$x_{33}$</td>
<td>33</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$w_1$</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>$w_2$</td>
<td>0.46</td>
<td>0.41</td>
<td>0.41</td>
</tr>
<tr>
<td>$w_3$</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>$w_4$</td>
<td>0.31</td>
<td>0.36</td>
<td>0.36</td>
</tr>
<tr>
<td>Objective</td>
<td>0.721</td>
<td>0.755</td>
<td>0.805</td>
</tr>
</tbody>
</table>

**Case 2:** With linear penalty function, the values for the decision variables in the numerical example are shown in Table 5:

\[
F(x_0) = \theta_0 x_{j0} = \theta_0 y_{j0} 
\]

\[
f_1 = (3x_{11} + 0.2x_{11}x_{12} + (2.6x_{12} + 0.15x_{12})x_{12} + (2.4x_{13} + 0.13x_{13})x_{13} + (3.5x_{21} + 0.19x_{21})x_{21} + (2.8x_{22} + 0.13x_{22})x_{22} + (2.4x_{23} + 0.13x_{23})x_{23} + (2.8x_{31} + 0.22x_{31})x_{31} + (2.5x_{32} + 0.16x_{32})x_{32} + (2.5x_{33} + 0.15x_{33})x_{33}
\]

**Case 3:** With non-linear penalty function, the values for the decision variables in the numerical example are shown in Table 6:

\[
F(x_0) = \theta_0 x_{j0} = \theta_0 y_{j0} 
\]

\[
f_1 = (3x_{11} + 0.2x_{11}x_{12} + (2.6x_{12} + 0.15x_{12})x_{12} + (2.4x_{13} + 0.13x_{13})x_{13} + (3.5x_{21} + 0.19x_{21})x_{21} + (2.8x_{22} + 0.13x_{22})x_{22} + (2.4x_{23} + 0.13x_{23})x_{23} + (2.8x_{31} + 0.22x_{31})x_{31} + (2.5x_{32} + 0.16x_{32})x_{32} + (2.5x_{33} + 0.15x_{33})x_{33}
\]

This example consists of other two objectives as follows:

\[
f_2 = 0.78x_{11}y_{11} + 0.83x_{12}y_{12} + 0.85x_{13}y_{13} + 0.8x_{21}y_{21} + 0.83x_{22}y_{22} + 0.87x_{23}y_{23} + 0.77x_{31}y_{31} + 0.8x_{32}y_{32} + 0.84x_{33}y_{33}
\]

\[
f_3 = 0.15x_{11}y_{11} + 0.12x_{12}y_{12} + 0.1x_{13}y_{13} + 0.15x_{21}y_{21} + 0.11x_{22}y_{22} + 0.1x_{23}y_{23} + 0.17x_{31}y_{31} + 0.13x_{32}y_{32} + 0.1x_{33}y_{33}
\]

Using Table 3, the membership functions for three objectives are provided by which the total cost is minimized, the net reliability is maximized and the net delay is minimized. The linear (nonlinear) programming software LINDO/LINGO is used to solve this problem. We can then get the following objective function and constraints:

\[
\text{max } \left\{ \frac{1}{k} \sum_{i=1}^{3} w_i \eta_i + \frac{1}{k} \sum_{i=4}^{4} w_i \mu_i \right\}
\]

s.t. \( \eta_i \leq \mu_i(x) \)

Case 3: With non-linear penalty function, the values for the decision variables in the numerical example are shown in Table 6:

\[
F(x_0) = \theta_0 x_{j0} = \theta_0 y_{j0} 
\]

\[
f_1 = (3x_{11} + 0.2x_{11}x_{12} + (2.6x_{12} + 0.15x_{12})x_{12} + (2.4x_{13} + 0.13x_{13})x_{13} + (3.5x_{21} + 0.19x_{21})x_{21} + (2.8x_{22} + 0.13x_{22})x_{22} + (2.4x_{23} + 0.13x_{23})x_{23} + (2.8x_{31} + 0.22x_{31})x_{31} + (2.5x_{32} + 0.16x_{32})x_{32} + (2.5x_{33} + 0.15x_{33})x_{33}
\]
In each of the three scenarios, the penalty function is different. Meanwhile, according to customer preferences such as single provider (\( \Sigma_3^1 = \Sigma_3^2 = 1 \)), multi-provider (\( \Sigma_3^1 = \Sigma_3^2 = \Sigma_3^3 = 1 \)) and random provider (\( \Sigma_3^1 = \Sigma_3^2 = \Sigma_3^3 > 1 \)), we analyze provider selection results that are shown in Tables 4–6. They disclose that variation in penalty function and customer preference will cause changes to the provider selection as well as the ordered quantities in service selection.

Using the model proposed in the previous section, Tables 4 and 5 reveal the optimal provider selection strategy when the missing data is unimportant and common. In two situations, customers can make the same decision. This implies that the result of provider selection is sometimes non-sensitive to the penalty function when the penalty is low. Meanwhile, based on the value of the objective, a multi-provider scenario is better than a single provider.

In Table 6, the customer receives the different results of provider selection because of the high penalty. It indicates that the penalty has sometimes large influence on the provider selection problem when the penalty cost by missing data is very high. Meanwhile, based on the value of the objective, the single provider scenario is better than the multi-provider.

On the basis of the results of Tables 4–6, we find a multi-provider scenario is not always better than a single provider. That is an important piece of information for customer. This explains why some customers still select one provider in some practical situations.

Moreover, our numerical example has also shown an interesting result for service provider selection. The example shows that the selected provider is not the cheapest provider or provider with the highest QoS level. In general, a firm should select the provider by balancing cost and QoS level. It means multi-criteria requirements should be simultaneously met.

At the same time, the example obviously shows providers who have the least expensive cost or the best QoS level sometimes can be forced out of the market if they cannot improve their overall competitive ability. Notably, from our numerical example, we find that our model enables the managers to select the most suitable provider for customers taking into consideration the multiple factors in a fuzzy environment.

### 7. Conclusions

Provider selection is one of the most important decision-making problems in e-commerce. In real situations, it is a multiple criteria decision-making problem in which the objectives and the constraints are not equally important. At the same time, during the course of decision making, input data are not precisely known. In this paper, a fuzzy multi-objective model involving multi-class services, penalty functions and penalty price breaks was developed for solving the problem of provider selection. This formulation can effectively handle the vagueness and imprecision of input data in provider selection problems.

Thus, the proposed model in this paper can help the users to choose the appropriate provider. Moreover, through translation, we transform the fuzzy multi-objective provider selection problem into a weighted max–min deterministic-crisp non-linear programming model. This transformation simplifies the solution process, giving less computational complexity, and makes the application of fuzzy methodology more understandable. Finally, from an application point of view, it is also worth for further investigating provider selection in different networks.

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### References


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- لیست مقالات ترجمه شده
- لیست مقالات ترجمه شده رایگان
- لیست جدیدترین مقالات انگلیسی

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