Int. J. Production Economics 147 (2014) 689–696

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

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

Wei Pan [a], Lean Yu [b,*], Shouyang Wang [c], Xianjia Wang [a]

[a] Economics and Management School, Wuhan University, Wuhan 430072, China
[b] School of Economics and Management, Beijing University of Chemical Technology, Beijing 100029, China
[c] Institute of Systems Science, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China

ARTICLE INFO

Article history:
Received 30 December 2010
Accepted 13 April 2013
Available online 2 May 2013

Keywords:
Fuzzy multi-objective optimization
Provider selection
QoS
Data communication

ABSTRACT

Data communication service has an important influence on e-commerce. The key challenge for the users is, ultimately, to select a suitable service provider. It is a multi-criteria decision-making (MCDM) problem where the user must weigh up the relative importance of factors such as costs and quality of service (QoS). Meanwhile, we know that in the real life situation, much of the input information is uncertain. Thus, the problem of provider selection becomes very complex in a real-life environment. In this paper, we combine these features to construct a new fuzzy multi-objective optimization model for solving the provider selection problem, considering non-linear objective membership function, multi-class services, price breaks, different QoS levels and penalty definition in different tasks. Finally, a numerical example is presented to illustrate the proposed method. The results show that this method is an effective method for solving the provider selection problem in data communication services.

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

* Corresponding author. Tel./fax: +8610 64438793.
E-mail address: yulean@amss.ac.cn (L. Yu).

0925-5273/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.ijpe.2013.04.030

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 simultaneously 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 tth provider, $t=1,2,\ldots,n$
p_{tj}	Price of the tth provider at jth price level, $j=1,2,\ldots,m_t$

V_{tj} Maximum demand quantity from the tth provider at jth price level
C_t Maximum capacity from the tth provider
V^*_{tj} A constant variable, slightly larger than V_{tj}
x_{tj} Transmission data quantity of user from the tth provider at the jth price level, $x_{tj} \in x$, where $x = \{x_{11}, x_{12}, \ldots, x_{nm_t}\}$
y_{tj} The decision variable determines if the tth provider at the jth price is selected or not, where $y_{tj} = 1$, if the tth provider is selected at the jth price level; otherwise $y_{tj} = 0$
θ_{tj} Missing rate of transmission data for the tth provider at the jth price level
$F(x_{tj})$ Penalty function of x_{tj}
L_{tj} Percentage of items that suffers delay in delivery for the tth provider at the jth price level
R_{tj} Percentage of reliable units for the tth provider at the jth price level
λ_p A parameter for the pth objective membership function, $\lambda_p > 0$
ε A coefficient for linear penalty function, $\varepsilon > 0$
ν, γ Coefficients for nonlinear penalty function, ν and γ 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:

$$\min f_d = \{f_1, f_2, \ldots, f_h\}, \tag{2.1}$$

$$\max f_e = \{f_{h+1}, f_{h+2}, \ldots, f_{q-h}\}, \tag{2.2}$$

with the following constraint:

$$g_i = \left\{ P\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} a_{it} x_{tj} \geq b_i \right\} \geq \beta_i \right\} \tag{2.3}$$

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 ith independent continuous random variable with given distributions, while a_{it} represents the coefficient of the tth decision variable in the ith constraint. β_i is the ith 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 β respectively represent the coefficient of the tth decision variable and the pre-assigned probability level in the demand constraint. Meanwhile, the tth provider can provide up to C_t units of the service over the planning period, i.e., $\sum_{j=1}^{m_t} x_{tj} \leq C_t$. This is due to service capacity. Then, we have that

$$P\left(\sum_{t=1}^{n} \sum_{j=1}^{m_t} d_t y_{tj} x_{tj} \geq D \right) \geq \beta. \tag{2.4}$$

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_{tj} is unimportant, the penalty function is equal to zero, i.e.,

$$F(x_{tj}) = 0. \tag{2.5}$$

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

$$F(x_{tj}) = \theta_{tj} x_{tj} \varepsilon. \tag{2.6}$$

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

$$F(x_{tj}) = \theta_{tj} x_{tj}^{\nu} \gamma. \tag{2.7}$$

The objective function for cost can be stated as follows:

$$f_1 = \sum_{t=1}^{n} \sum_{j=1}^{m_t} \{p_{tj} y_{tj} x_{tj} + F(x_{tj})\} \tag{2.8}$$

which should minimize the cost of service.

The objective function for reliability is defined as

$$f_2 = \sum_{t=1}^{n} \sum_{j=1}^{m_t} R_{tj} y_{tj} x_{tj} \tag{2.9}$$

which should maximize the number of reliable units.

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

$$f_3 = \sum_{t=1}^{n} \sum_{j=1}^{m_t} L_{tj} y_{tj} x_{tj} \tag{2.10}$$

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:

$$f_1^* = \min\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} \{p_{tj} y_{tj} x_{tj} + F(x_{tj})\} \right\}, \quad \text{(cost)}$$
$$f_2^* = \max\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} R_{tj} y_{tj} x_{tj} \right\}, \quad \text{(reliability)}$$
$$f_3^* = \min\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} L_{tj} y_{tj} x_{tj} \right\}, \quad \text{(delay)}$$
$$P\left(\sum_{t=1}^{n} \sum_{j=1}^{m_t} d_t y_{tj} x_{tj} \geq D \right) \geq \beta, \quad \text{(demand)}$$
$$\sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} = 1, \quad \text{(single provider selected)}$$
$$\sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} > 1, \quad \text{(multi} - \text{provider selected)}$$
$$\sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} \geq 1, \quad \text{(random provider selected)}$$
$$\sum_{j=1}^{m_t} y_{tj} \leq 1, \quad y_{tj} \in \{0, 1\},$$
$$V^*_{tj} = V_{tj} + 1,$$
$$y_{tj} V^*_{t(j-1)} \leq x_{tj} \leq y_{tj} V_{tj}, \quad x_{tj} \geq 0,$$
$$\sum_{j=1}^{m_t} x_{tj} \leq C_t.$$

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 "≳" in the objectives and constraints indicate fuzziness of "≥", i.e., approximately greater than or equal to. In contrast, "≲" 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:

$$f(d) \lesssim \tilde{f}_d, \quad d = 1, 2, \ldots, h, \tag{3.1}$$

$$f(e) \gtrsim \tilde{f}_e, \quad e = 1, 2, \ldots, q-h, \tag{3.2}$$

$$P\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} a_{it} y_{tj} x_{tj} \gtrsim b_i \right\} \gtrsim \beta_i, \quad i = 1, 2, \ldots, m, \tag{3.3}$$

$$\sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} = 1, \quad \text{or} \quad \sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} > 1, \quad \text{or} \quad \sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} \geq 1, \tag{3.4}$$

$$V_{tj}^{*} = V_{tj} + 1, \tag{3.5}$$

$$y_{tj} V_{t(j-1)}^{*} \leq x_{tj} \leq y_{tj} V_{tj}, \tag{3.6}$$

$$\sum_{j=1}^{m_t} y_{tj} \leq 1, \quad y_{tj} \in \{0, 1\}, \tag{3.7}$$

$$\sum_{j=1}^{m_t} x_{tj} \leq C_t, \quad x_{tj} \geq 0, \tag{3.8}$$

where a_{it}, b_i and β_i respectively are the coefficient of the tth decision variable in the ith constraint, the ith independent continuous random variable with given distributions, and the ith preassigned probability level defined in Section 3.

By considering c_{it} and δ_i, where $c_{it} > 0$ 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

$$P\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} a_{it} y_{tj} x_{tj} \geq b_i \right\} \geq \beta_i. \tag{3.9}$$

The decision-maker is almost satisfied if

$$\delta_i < P\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} a_{it} y_{tj} x_{tj} \geq b_i \right\} < \beta_i,$$

or

$$P\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} (a_{it} + c_{it}) y_{tj} x_{tj} \geq b_i \right\} \geq \beta_i. \tag{3.10}$$

The decision-maker is not satisfied if

$$P\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} a_{it} y_{tj} x_{tj} \geq b_i \right\} \leq \delta_i,$$

or

$$P\left\{ \sum_{t=1}^{n} \sum_{j=1}^{m_t} (a_{it} + c_{it}) y_{tj} x_{tj} \geq b_i \right\} < \beta_i. \tag{3.11}$$

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

$$\sum_{t=1}^{n} \sum_{j=1}^{m_t} a_{it} y_{tj} x_{tj} \geq F_i^{-1}(\beta_i), \tag{3.12}$$

$$F_i^{-1}(\delta_i) < \sum_{t=1}^{n} \sum_{j=1}^{m_t} a_{it} y_{tj} x_{tj} < F_i^{-1}(\beta_i),$$

or

$$F_i^{-1}(\beta_i) \leq \sum_{t=1}^{n} \sum_{j=1}^{m_t} (a_{it} + c_{it}) y_{tj} x_{tj}, \tag{3.13}$$

$$\sum_{t=1}^{n} \sum_{j=1}^{m_t} a_{it} y_{tj} x_{tj} \leq F_i^{-1}(\delta_i),$$

or

$$\sum_{t=1}^{n} \sum_{j=1}^{m_t} (a_{it} + c_{it}) y_{tj} x_{tj} < F_i^{-1}(\beta_i) \tag{3.14}$$

where $F_i^{-1}(\cdot)$ is the inverse of the cumulative distribution function $F_i(\cdot)$, $i = 1, 2, \ldots, m$.

Let f_p and g_i be the functions of objectives and constraints, respectively. Using the Bellman–Zadeh approach (Zadeh, 1975), the fuzzy set objective functions and constraints are defined by

$$f_p = \{x, \mu_{f_p}\}, \quad g_i = \{x, \mu_{g_i}\}, \quad p = 1, 2, \ldots, q \tag{3.15}$$

where $\mu_{f_p}, \mu_{g_i} | x \longrightarrow [0, 1]$ are the degree of membership to which x belongs to objectives and constraints, where $x = \{x_{11}, x_{12}, \ldots, x_{nm_t}\}$.

The fuzzy set objectives and constraints are thus uniquely determined by objectives and constraints membership functions μ_{f_p} and μ_{g_i}, respectively. The range of membership functions μ_{f_p} and μ_{g_i} is a subset of the non-negative real numbers whose value is finite and usually finds a place in the interval [0, 1].

Let μ_D represent the membership function of the solution. Using Eq. (3.15), it is possible to obtain the solution proving the maximum degree as follows:

$$\max \mu_D = \max\left\{ \min_{1 \leq p \leq q} \mu_{f_p}, \min_{1 \leq i \leq m} \mu_{g_i} \right\}, \tag{3.16}$$

$$x^0 = \arg\max\left\{ \min_{1 \leq p \leq q} \mu_{f_p}, \min_{1 \leq i \leq m} \mu_{g_i} \right\}. \tag{3.17}$$

Finally, to obtain Eqs. (3.16) and (3.17), it is necessary to build membership functions μ_{f_p} and μ_{g_i} by the corresponding f_p and g_i. For maximizing objective functions, we use the following membership functions:

$$\mu_{f_p} = \begin{cases} 1, & f_p \geq \max f_p \\ \left\{ \dfrac{f_p - \min f_p}{\max f_p - \min f_p} \right\}^{\lambda_p}, & \min f_p < f_p < \max f_p \\ 0, & f_p \leq \min f_p \end{cases} \tag{3.18}$$

For minimized objective functions, we use the following membership functions:

$$\mu_{f_p} = \begin{cases} 1, & f_p \leq \min f_p \\ \left\{ \dfrac{\max f_p - f_p}{\max f_p - \min f_p} \right\}^{\lambda_p}, & \min f_p < f_p < \max f_p \\ 0, & f_p \geq \max f_p \end{cases} \tag{3.19}$$

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

$$f_p \to \min f_p, \tag{3.20}$$

$$f_p \to \max f_p \tag{3.21}$$

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

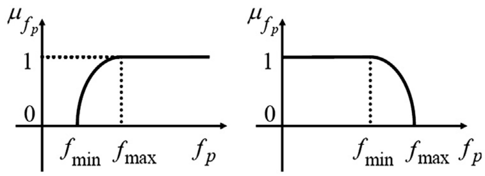

Fig. 1. The different membership functions.

membership function μ_{f_p} as presented in Eq. (3.18) or (3.19) (see Fig. 1).

Eq. (3.22) is a membership function of fuzzy values of linguistic variables which reflect constraints of qualitative character:

$$\mu_{g_i} = \begin{cases} 1, & \sum_{t=1}^{n}\sum_{j=1}^{m_t} a_{it}y_{tj}x_{tj} \geq F_i^{-1}(\beta_i) \\ \min\{k_i, h_i\}, & F_i^{-1}(\delta_i) < \sum_{t=1}^{n}\sum_{j=1}^{m_t} a_{it}y_{tj}x_{tj} < F_i^{-1}(\beta_i) \\ & \leq \sum_{t=1}^{n}\sum_{j=1}^{m_t} (a_{it}+c_{it})y_{tj}x_{tj} \\ 0, & \sum_{t=1}^{n}\sum_{j=1}^{m_t} a_{it}y_{tj}x_{tj} \leq F_i^{-1}(\delta_i) \\ & \text{or } \sum_{t=1}^{n}\sum_{j=1}^{m_t} (a_{it}+c_{it})y_{tj}x_{tj} < F_i^{-1}(\beta_i) \end{cases} \tag{3.22}$$

where k_i and h_i are defined by

$$k_i = \frac{\sum_{t=1}^{n}\sum_{j=1}^{m_t} a_{it}y_{tj}x_{tj} - F_i^{-1}(\delta_i)}{F_i^{-1}(\beta_i) - F_i^{-1}(\delta_i)}, \tag{3.23}$$

$$h_i = \frac{\sum_{t=1}^{n}\sum_{j=1}^{m_t} (a_{it}+c_{it})y_{tj}x_{tj} - F_i^{-1}(\beta_i)}{\sum_{t=1}^{n}\sum_{j=1}^{m_t} c_{it}y_{tj}x_{tj}},$$

$$\sum_{t=1}^{n}\sum_{j=1}^{m_t} c_{it}y_{tj}x_{tj} \neq 0. \tag{3.24}$$

On the other hand, if

$$P\left\{\sum_{t=1}^{n}\sum_{j=1}^{m_t} a_{it}y_{tj}x_{tj} \leq b_i\right\} \geq \beta_i, \tag{3.25}$$

then

$$k_i = \frac{F_i^{-1}(1-\delta_i) - \sum_{t=1}^{n}\sum_{j=1}^{m_t} a_{it}y_{tj}x_{tj}}{F_i^{-1}(1-\delta_i) - F_i^{-1}(1-\beta_i)}, \tag{3.26}$$

$$h_i = \frac{F_i^{-1}(1-\beta_i) - \sum_{t=1}^{n}\sum_{j=1}^{m_t} (a_{it}-c_{it})y_{tj}x_{tj}}{\sum_{t=1}^{n}\sum_{j=1}^{m_t} c_{it}y_{tj}x_{tj}},$$

$$\sum_{t=1}^{n}\sum_{j=1}^{m_t} c_{it}y_{tj}x_{tj} \neq 0. \tag{3.27}$$

4. Decision making process

In this section, we present a decision making process. Firstly, we discuss the max–min operator, which was used by Zimmermann for fuzzy multi-objective problems (Zimmermann, 1987, 1993). Then, we show the convex (weighted additive) operator, which enables the decision maker to assign different weights to various criteria.

In fuzzy programming modeling, using Zimmermann's approach, a fuzzy solution is given by the intersection of all the fuzzy sets representing either fuzzy objectives or fuzzy constraints. The fuzzy solution for all fuzzy objectives and fuzzy constraints may be given as follows:

$$\mu_D = \left\{ \bigcap_{p=1}^{q} \mu_{f_p}, \quad \bigcap_{i=1}^{m} \mu_{g_i} \right\} \tag{4.1}$$

where μ_D, μ_{f_p} and μ_{g_i} are defined in Section 4, q is the number of objectives, m is the number of constrains.

The optimal solution μ_D^* for all fuzzy objectives and fuzzy constraints is given as follows:

$$\mu_D^* = \max\{\mu_D\}. \tag{4.2}$$

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 kth 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:

$$\mu_D = \sum_{k=1}^{q} w_k \eta + \sum_{k=q+1}^{q+m} w_k \kappa, \tag{4.3}$$

$$\sum_{p=1}^{q} w_{f_p} + \sum_{i=1}^{m} w_{g_i} = 1, \quad w_{f_p}, w_{g_i} \geq 0 \tag{4.4}$$

where w_{f_p} and w_{g_i} are the weighting coefficients that present the relative importance among the fuzzy goals and the fuzzy constraints, respectively. η and κ 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 integrate 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:

$$\max\{\tilde{w}_{f_p}\eta + \tilde{w}_{g_i}\kappa\}, \tag{4.5}$$

$$\eta \leq \mu_{f_p}, \tag{4.6}$$

$$\kappa \leq \mu_{g_i} \tag{4.7}$$

where $\tilde{w}_{f_p}$ and $\tilde{w}_{g_i}$ are the fuzzy weighting coefficients that present the relative importance among the fuzzy goals and the fuzzy constraints, respectively.

Let $\tilde{w}_k = \{\underline{w_k}, w_{k1}, w_{k2}, \overline{w_k}\}$ be a trapezoidal fuzzy number, or let $\tilde{w}_k = \{\underline{w_k}, w_{k0}, \overline{w_k}\}$ be a triangular fuzzy number, where $\underline{w_k}$ and $\overline{w_k}$ are the minimal value and the maximal value, respectively.

It is noticed that, w_k is a decision variable, in addition to η, κ, x_{tj} and y_{tj}. 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 α 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 $\tilde{w}_k$, 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:

$$\max \left\{ \sum_{k=1}^{q} w_k \eta_k + \sum_{k=q+1}^{q+m} w_k \kappa_k \right\}, \tag{4.8}$$

$$\text{s.t.} \quad \eta_p \le \mu_{f_p}, \tag{4.9}$$

$$\kappa_i \le \mu_{g_i}, \tag{4.10}$$

$$\underline{w_k}(1-\alpha) + w_{k1} \le w_k \le \overline{w_k}(1-\alpha) + w_{k2}, \tag{4.11}$$

$$\sum_{k=1}^{q+m} w_k = \sum_{p=1}^{q} w_{f_p} + \sum_{i=1}^{m} w_{g_i} = 1, \quad w_{f_p}, w_{g_i} \ge 0, \tag{4.12}$$

$$\sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} = 1, \quad \text{or} \quad \sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} > 1, \text{ or } \sum_{t=1}^{n} \sum_{j=1}^{m_t} y_{tj} \ge 1, \tag{4.13}$$

$$V^*_{tj} = V_{tj} + 1, \tag{4.14}$$

$$y_{tj} V^*_{t(j-1)} \le x_{tj} \le y_{tj} V_{tj}, \tag{4.15}$$

$$x_{tj} \ge 0, \quad \sum_{j=1}^{m_t} x_{tj} \le C_t, \tag{4.16}$$

$$\sum_{j=1}^{m_t} y_{tj} \le 1, \quad y_{tj} \in \{0, 1\}. \tag{4.17}$$

The decision-maker has to set the value of α, 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 $\sum_{k=1}^{q+m} w_k = 1$.

On the other hand, if $\tilde{w}_k$, for any jth objective or constraint, is considered as a triangular fuzzy number, then w_{k1} and w_{k2} should be replaced by w_{k0}, for the kth 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_i and w_k 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 α.

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, $d_t = 1$, $\varepsilon = \gamma = \lambda_p = 1$, $\beta = 0.8$, $\nu = 2$, $\alpha = 0.1$.

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:

$$F(x_{tj}) = 0,$$

$$f_1 = 3x_{11}y_{11} + 2.6x_{12}y_{12} + 2.4x_{13}y_{13} + 3.5x_{21}y_{21} + 2.8x_{22}y_{22} + 2.4x_{23}y_{23} + 2.8x_{31}y_{31} + 2.5x_{32}y_{32} + 2.2x_{33}y_{33}.$$

Table 1
Collected data for numerical example.

Provider	*Quantity*	*Price*	*Loss*	*Reliability*	*Delay*	*Capacity*
1	$0 \le x_{11} \le 16$	3	0.2	0.78	0.15	50
	$17 \le x_{12} \le 32$	2.6	0.15	0.83	0.12	
	$33 \le x_{13}$	2.4	0.13	0.85	0.1	
2	$0 \le x_{21} \le 16$	3.5	0.19	0.8	0.15	48
	$17 \le x_{22} \le 32$	2.8	0.13	0.83	0.11	
	$33 \le x_{23}$	2.4	0.1	0.87	0.1	
3	$0 \le x_{31} \le 16$	2.8	0.22	0.77	0.17	47
	$17 \le x_{32} \le 32$	2.5	0.16	0.8	0.13	
	$33 \le x_{33}$	2.2	0.15	0.84	0.1	

Table 2
Weight value.

$\tilde{w}_1$	0.1	0.2	0.4	0.8
$\tilde{w}_2$	0.4	0.5	0.6	0.9
$\tilde{w}_3$	0.1	0.3	0.4	0.8
$\tilde{w}_4$	0.3	0.4	0.6	0.8

Table 3
The lower bounds and upper bounds value of the objective functions under different customer preferences.

Objective	y_{tj}	$\mu_f = 0$	$\mu_f = 1$
	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$	72.6	89.6
f_1	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$	72.6	140.4
(*no penalty*)	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \geq 1$	72	140.4
	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$	75.55	93.76
f_1	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$	75	149.5
(*linear loss*)	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \geq 1$	71.84	149.5
	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$	188.1	243.84
f_1	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$	136.88	282.99
(*nonlinear loss*)	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \geq 1$	140.69	308.25
	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$	24	26.56
f_2	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$	23.24	39.15
(*reliability*)	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \geq 1$	23.24	39.15
	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$	3	4.16
f_3	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$	3.3	7.07
(*delay*)	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \geq 1$	3.3	6.17

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

No penalty	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \geq 1$
x_{11}	0	1	0
x_{12}	0	0	0
x_{13}	0	0	0
x_{21}	0	0	0
x_{22}	0	0	0
x_{23}	0	44	45
x_{31}	0	0	0
x_{32}	0	0	0
x_{33}	33	0	0
w_1	0.11	0.11	0.11
w_2	0.46	0.41	0.41
w_3	0.12	0.12	0.12
w_4	0.31	0.36	0.36
Objective	0.721	0.899	0.892

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

$$F(x_{tj}) = \theta_{tj} x_{tj} \varepsilon = \theta_{tj} x_{tj},$$

$$\begin{aligned} f_1 = {} & (3x_{11} + 0.2x_{11})y_{11} + (2.6x_{12} + 0.15x_{12})y_{12} \\ & + (2.4x_{13} + 0.13x_{13})y_{13} \\ & + (3.5x_{21} + 0.19x_{21})y_{21} + (2.8x_{22} + 0.13x_{22})y_{22} + (2.4x_{23} + 0.1x_{23})y_{23} \\ & + (2.8x_{31} + 0.22x_{31})y_{31} + (2.5x_{32} + 0.16x_{32})y_{32} + (2.2x_{33} + 0.15x_{33})y_{33}. \end{aligned}$$

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

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

Linear penalty	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \geq 1$
x_{11}	0	1	0
x_{12}	0	0	0
x_{13}	0	0	0
x_{21}	0	0	0
x_{22}	0	0	0
x_{23}	0	44	45
x_{31}	0	0	0
x_{32}	0	0	0
x_{33}	33	0	0
w_1	0.11	0.11	0.11
w_2	0.46	0.41	0.41
w_3	0.12	0.12	0.12
w_4	0.31	0.36	0.36
objective	0.709	0.901	0.892

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

Non-linear penalty	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$	$\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \geq 1$
x_{11}	0	1	0
x_{12}	0	0	0
x_{13}	0	33	0
x_{21}	0	11	0
x_{22}	0	0	0
x_{23}	0	0	44
x_{31}	0	0	0
x_{32}	0	0	0
x_{33}	33	0	0
w_1	0.11	0.11	0.11
w_2	0.46	0.41	0.41
w_3	0.12	0.12	0.12
w_4	0.31	0.36	0.36
objective	0.721	0.755	0.805

$$F(x_{tj}) = \theta_{tj} x_{tj}^{\nu} \gamma = \theta_{tj} x_{tj}^2,$$

$$\begin{aligned} f_1 = {} & (3x_{11} + 0.2x_{11}^2)y_{11} + (2.6x_{12} + 0.15x_{12}^2)y_{12} \\ & + (2.4x_{13} + 0.13x_{13}^2)y_{13} + (3.5x_{21} + 0.19x_{21}^2)y_{21} \\ & + (2.8x_{22} + 0.13x_{22}^2)y_{22} + (2.4x_{23} + 0.1x_{23}^2)y_{23} \\ & + (2.8x_{31} + 0.22x_{31}^2)y_{31} + (2.5x_{32} + 0.16x_{32}^2)y_{32} \\ & + (2.2x_{33} + 0.15x_{33}^2)y_{33}. \end{aligned}$$

This example consists of other two objectives as follows:

$$\begin{aligned} f_2 = {} & 0.78x_{11}y_{11} + 0.83x_{12}y_{12} + 0.85x_{13}y_{13} + 0.8x_{21}y_{21} + 0.83x_{22}y_{22} \\ & + 0.87x_{23}y_{23} + 0.77x_{31}y_{31} + 0.8x_{32}y_{32} + 0.84x_{33}y_{33}, \\ f_3 = {} & 0.15x_{11}y_{11} + 0.12x_{12}y_{12} + 0.1x_{13}y_{13} + 0.15x_{21}y_{21} + 0.11x_{22}y_{22} \\ & + 0.1x_{23}y_{23} + 0.17x_{31}y_{31} + 0.13x_{32}y_{32} + 0.1x_{33}y_{33}. \end{aligned}$$

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:

$$\max \left\{ \sum_{k=1}^{3} w_k \eta_k + \sum_{k=4}^{4} w_k \kappa_k \right\},$$

$$\text{s.t.} \quad \eta_p \leq \mu_{f_p}(x), \quad \kappa_i \leq \mu_{g_i}(x), \quad 0.11 \leq w_1 \leq 0.76, \quad 0.41 \leq w_2 \leq 0.87,$$
$$0.12 \leq w_3 \leq 0.76, \quad 0.31 \leq w_4 \leq 0.78, \quad w_1 + w_2 + w_3 + w_4 = 1,$$

$$V_{11}^* = V_{21}^* = V_{31}^* = 17, \quad V_{12}^* = V_{32}^* = V_{33}^* = 33,$$
$$\sum_{j=1}^{3} y_{tj} \le 1, \quad y_{tj} \in \{0,1\}, \quad x_{tj} \ge 0, \sum_{j=1}^{3} x_{1j} \le 50, \sum_{j=1}^{3} x_{2j} \le 48,$$
$$\sum_{j=1}^{3} x_{3j} \le 47, \sum_{t=1}^{3}\sum_{j=1}^{3} x_{tj} \le 45.$$

In each of the three scenarios, the penalty function is different. Meanwhile, according to customer preferences such as single provider ($\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} = 1$), multi-provider ($\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} > 1$) and random provider ($\sum_{t=1}^{3}\sum_{j=1}^{3} y_{tj} \ge 1$), 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.

Acknowledgments

This work is partially supported by grants from the National Science Fund for Distinguished Young Scholars (NSFC No. 71025005), the National Natural Science Foundation of China (NSFC nos. 90924024, 91224001, 71231007 and 71101060) and, the Knowledge Innovation Program of the Chinese Academy of Sciences and the Fundamental Research Funds for the Central Universities (No.1101012), Post-1970 Young Scholars in Humanities and Social Sciences from Wuhan University, Training Program of High Level International Journal Articles in Humanities and Social Sciences from Wuhan University.

References

Ahsan, S.M., 2006. A framework for QoS computation in web service and technology selection. Computer Standards and Interfaces 28, 714–720.
Amida, A., Ghodsypour, S., O'Brien, C., 2009. A weighted additive fuzzy multi-objective model for the supplier selection problem under price breaks in a supply chain, International Journal of Production Economics 121, 323–332.
Amida, A., Ghodsypour, S., O'Brien, C., 2006. Fuzzy multiobjective linear model for supplier selection in a supply chain. International Journal of Production Economics 104, 394–407.
Armony, M., Haviv, M., 2003. Price and delay competition between two service providers. European Journal of Operational Research 147, 32–50.
Comer, D.E., 2001. Computer Networks and Internets with Internet Applications, 3rd ed.. Prentice Hall.
Ghobadian, A., Stainer, A., Kiss, T., 1993. A computerized vendor rating system. Proceedings of the First International Symposium on Logistics, July 1993, The University of Nottingham, Nottingham, UK, pp. 321–328.
Hwang, C., Masud, A., 1979. Multiple Objective Decision Making Methods and Application: A State of Art Survey. Springer-Verlag.
Kasap, N., Aytug, H., Erengu, S.S., 2007. Provider selection and task allocation issues in networks with different QoS levels and all you can send pricing. Decision Support Systems 43, 375–389.
Kumara, M., Vratb, P., Shankar, R., 2006. A fuzzy programming approach for vendor selection problem in a supply chain. International Journal of Production Economics 101, 273–285.
Lia, J., Xua, J., Genb, M., 2006. A class of multiobjective linear programming model with fuzzy random coefficients. Mathematical and Computer Modelling 44, 1097–1113.
Pan, W., Wang, S., Zhang, J., Hua, G., Fang, Y., 2008. Fuzzy multi-objective order allocation model for risk management in a supply chain. In: Proceedings of Second Asia International Conference on Modelling and Simulation, pp. 771–776.
Raghuram, M., Munindar, P., 2004. Agent-based service selection. Web Semantics: Science, Services and Agents on the World Wide Web 1, 261–279.
Ragsdale, G.L., Lynch, G.P., Raschke, M.W., 2000. The convergence of signaling system 7 and voice-over-IP. Project Report (SWRI project No. 10.03607). Southwest Research Institute, 2000.
Sakawa, M., 1993. Fuzzy Sets and Interactive Multiobjective Optimization. Plenum Press.
Teitelbaum, B., Sadagic, A., 2002. Internet QoS and video: sharing responsibility to overcome congestion-related performance problems. In: Proceedings of SURA/VIDE 4th Annual Digital Video Workshop, pp. 1–32.
Tiwari, R., Dharmahr, S., Rao, J., 1987. Fuzzy goal programming-an additive model. Fuzzy Sets and Systems 24, 27–34.
Wang, H., Lee, C., Ho, T., 2007. Combining subjective and objective QoS factors for personalized web service selection. Expert Systems with Applications 32, 571–584.
Wang, M., Liu, J., Wang, H., Cheung, W.K., Xie, X., 2008. On-demand e-supply chain integration: a multi-agent constraint-based approach. Expert Systems with Applications 34, 2683–2692.
Zadeh, L., 1975. The concept of a linguistic variable and its application to approximate reasoning. Information Sciences 8, 301–357.
Zimmermann, H., 1987. Fuzzy Sets, Decision Making and Expert Systems. Kluwer Academic Publishers.
Zimmermann, H., 1993. Fuzzy Set Theory and its Applications, 4th ed.. Kluwer Academic Publishers.