International Journal of Innovative Computing, Information and Control
Volume **10**, Number **6**, December **2014**

ICIC International ©2014 ISSN 1349-4198
pp. **2251–2262**

FUZZY QOS-DRIVEN SERVICE SELECTION METHOD FOR GROUP USER

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Received January 2014; revised May 2014

Abstract. *The selection of software as a service (SaaS) for group user in cloud service provision is challenging, notably because the quality of service (QoS) of SaaS and the personalization QoS preference of members in group are uncertain. This is an urgent problem and it will increase its importance with the advent of the SaaS model of service delivery. Therefore, in choosing the cloud service of SaaS to utilize for group user, the alternatives must be ranked based on the QoS of services and members' QoS preference expressed by fuzzy terms. In order to identify their dissimilarity on alternatives, and assist group user in selecting most suitable service with consideration of the members' preferences in group, a fuzzy QoS-driven service selection method for group user (FQSS_GU) is proposed based on multiple attributes decision making (MADM) theory. This approach can obtain the group optimal solution when the QoS preference of member in group is personalized with uncertainty and the QoS of alternatives is expressed by fuzzy terms. Finally, four experiments are given to demonstrate the benefits and effectiveness of fuzzy QoS-driven service selection method. The experimental results demonstrated that it is a feasible and supplementary manner in selecting the cloud service of SaaS for group user.*
Keywords: Software as a service (SaaS), Cloud service, Service selection, Quality of service (QoS), Multiple attributes decision making (MADM), Group user

1. **Introduction.** Software as a service (SaaS), sometimes referred to as "on-demand software", is a software delivery model in which software and associated data are centrally hosted on the cloud. By reducing the cost of ownership and alleviating the burden of software installation and maintenance, SaaS has gained popularity in recent years. As enterprises have started to outsource some of their software infrastructure and development projects to SaaS vendors, the number of SaaS offerings has expanded dramatically, even among vendors of traditional on-premises software [1].

However, integrating outsourced software into project development can be challenging. In particular, the QoS of the external software may not be satisfactory. SaaS somewhat lowers this risk due to its on-use pricing and provides users with a looser, more flexible relationship to software or service providers. To some extent, SaaS provides a low-risk alternative to large investments. Nevertheless, the success of SaaS integration depends on the behavior of the provider and user's preference. Since the software is being delivered as a service, it is hosted at the provider, and similarly maintained by the provider, leaving the consumer with a low degree of control on its performance. As long as the service provider fulfills its obligations to the consumer that it provides the needed support, undertakes the required management and maintenance tasks, and generally behaves well, so the risks of failure remain low. However, the behavior of service providers is unknown until the service is rendered. The risk of bad behavior cannot be excluded and can have adverse effects on the project outcomes. Users and providers may have different expectations and experiences about the services, so the evaluations on services from users are creditable (assuming the users are honest). However, it is difficult for users to describe imprecisely the QoS of services. Moreover, users usually have distinct view with providers for service terms, such as "low cost travel agent service", "high availability travel agent service", simply because they have divergent perception of these terms.

The users' preferences often remain imprecise, uncertain or ambiguous on services QoS attributes; the preferences over the QoS criteria are hard to be quantified especially in distinguishing the importance among these service attributes [2]. Therefore, the adoption of fuzzy terms such as very unimportant cost, very important availability, important reliability and unimportant reputation in the requests becomes inevitable. In addition, the members' QoS preferences in group may be different (named personalized QoS preference), for instance, the QoS preference of member A is very unimportant cost, very important availability, important reliability and unimportant reputation and member B is very important cost, very unimportant availability, unimportant reliability and important reputation. Figure 1 shows fuzzy QoS-driven service selection process for group user, which is our research motivation.

To attack this critical challenge, we propose a multiple attributes decision making theory based approach (named FQSS_GU) for selecting optimal SaaS for group user. Compared fuzzy TOPSIS [21], the contribution of this paper is three-fold. First, we propose a fuzzy QoS criterion description method by fuzzy terms from users' feedback. Second, we propose a fuzzy preference-oriented service ranking approach for group user. Users' QoS preference and group weight are expressed by fuzzy terms. Users' QoS preference reflects the requirements on QoS. Group weight reflects the importance of users in group. Third, we propose FQSS_GU, which considered the service selection for group user where the members' QoS preference in group and the QoS of services expressed by fuzzy terms, can gain group QoS optimal service. FQSS_GU not only enhances user satisfaction but also reduces the risk of service integration.

This paper is organized as follows. Section 2 introduces our service selection method-FQSS_GU. Section 3 shows the implementation and experiments. Finally, we discuss related work in Section 4 and conclude in Section 5.

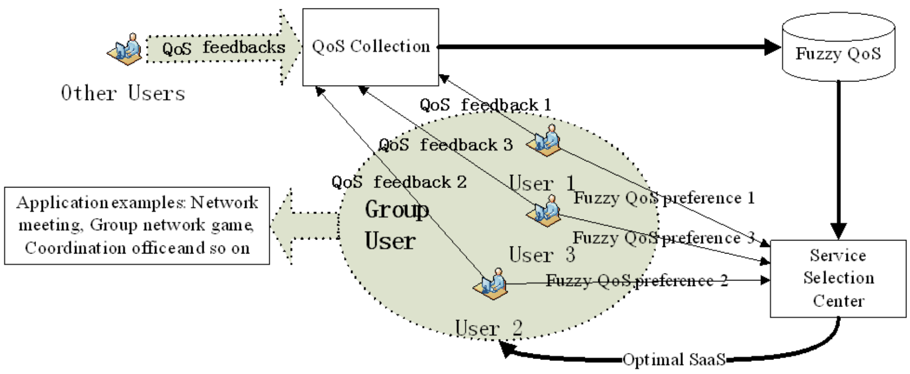

Figure 1. Fuzzy QoS-driven service selection process for group user

2. **The Proposed Method for Ranking SaaS Services (FQSS_GU).** In this section, we introduce a fuzzy QoS-driven service selection method based on TOPSIS for group user (FQSS_GU). FQSS_GU is a new fuzzy multiple attributes group decision making method, which extends TOPSIS. In FQSS_GU, the performance ratings matrix given by decision maker is replaced by member performance rating matrix. To obtain more reasonable ranking results, the normalization decision matrix and the determining of fuzzy positive/negative ideal solution are optimization.

2.1. **Problem formulation.** Consider the problem of ranking service alternatives a_i $(i = 1, \cdots, m)$, and there are n QoS attributes in a_i, identified by p_j $(j = 1, \cdots, n)$. There are q members $(c_k\ (k = 1, \cdots, q))$ in group user; they share the same service. Each member has to assign his QoS preference ω_{kj}, and ω_{kj} are TFNs chosen from Table 1 that represents the importance of service a_i with respect to criterion p_j for member c_k. If ω_{kj} is a fuzzy data expressed by fuzzy terms, then it must be converted to a triangular fuzzy number (TFN) in the form of $(\underline{a}, a, \bar{a})$ in Ref. [19], where $\underline{a}, a, \bar{a}$ are real numbers and $\underline{a} \le a \le \bar{a}$. The performance rating matrix $\tilde{X}$ for service alternatives is shown as Equation (1), where $\tilde{x}_{ij}$ are TFNs chosen from Table 2 that represents the rating of service a_i with respect to attribute p_j. Table 1 and Table 2 describe the fuzzy terms corresponding triangular fuzzy numbers, which is set by the experts according to the actual situation. The number of fuzzy terms and TFNs is less and the TFNs may increase or decrease. In the future, we will develop an automated tool to collect the QoS data and users QoS preferences.

$$\tilde{X} = [\tilde{x}_{ij}]_{m\times n} = \begin{array}{c|cccc} & p_1 & p_2 & \cdots & p_n \\ \hline a_1 & \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ a_2 & \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_3 & \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{array} \tag{1}$$

If the QoS preferences of any two members in group are not completely consistent, then the performance rating matrix $\tilde{X}(c_k)$ is calculated for member c_k shown as Equation (2).

$$\tilde{X}(c_k) = [\tilde{x}_{ij}(c_k)]_{m\times n} = \begin{array}{c|cccc} & p_1 & p_2 & \cdots & p_n \\ \hline a_1 & \omega_{k1}\otimes\tilde{x}_{11} & \omega_{k2}\otimes\tilde{x}_{12} & \cdots & \omega_{kn}\otimes\tilde{x}_{1n} \\ a_2 & \omega_{k1}\otimes\tilde{x}_{21} & \omega_{k2}\otimes\tilde{x}_{22} & \cdots & \omega_{kn}\otimes\tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_m & \omega_{k1}\otimes\tilde{x}_{m1} & \omega_{k2}\otimes\tilde{x}_{m2} & \cdots & \omega_{kn}\otimes\tilde{x}_{mn} \end{array} \tag{2}$$

If the QoS preferences of members are the same, then they have the same performance rating matrix. While the QoS preferences of members are not the same, then each member has a performance rating matrix in group. So the QoS-optimal service for group needs

TABLE 1. Fuzzy terms for the importance of attribute

Fuzzy terms	Very unimportant (VU)	Unimportant (U)	Medium (M)	Important (I)	Very important (VI)
TFNs	(0,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,10)

TABLE 2. Fuzzy terms for the performance rating of each alternative

Fuzzy terms	Very low (VL)	Low (L)	Fair (F)	High (H)	Very High (VH)
TFNs	(0,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,10)

to be gained according to the importance of members (named group weight) in group. The leader of group assigns w_k, w_k is TFNs chosen from Table 1 that represents the importance of member c_k in group (named group weight). The performance rating matrix $\tilde{X}(c_k)$ considered the importance of service consumer in group is calculated for service consumer shown as Equation (3).

$$\tilde{X}(c_k) = [\tilde{x}_{ij}(c_k)]_{m\times n} = \begin{array}{c|cccc} & p_1 & p_2 & \cdots & p_n \\ \hline a_1 & w_k \otimes (\omega_{k1} \otimes \tilde{x}_{11}) & w_k \otimes (\omega_{k2} \otimes \tilde{x}_{12}) & \cdots & w_k \otimes (\omega_{kn} \otimes \tilde{x}_{1n}) \\ a_2 & w_k \otimes (\omega_{k1} \otimes \tilde{x}_{21}) & w_k \otimes (\omega_{k2} \otimes \tilde{x}_{22}) & \cdots & w_k \otimes (\omega_{kn} \otimes \tilde{x}_{2n}) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_m & w_k \otimes (\omega_{k1} \otimes \tilde{x}_{m1}) & w_k \otimes (\omega_{k2} \otimes \tilde{x}_{m2}) & \cdots & w_k \otimes (\omega_{kn} \otimes \tilde{x}_{mn}) \end{array} \quad (3)$$

2.2. **Evaluating fuzzy synthetic performances.** Once the QoS preference of member for each QoS attribute is assigned and the group weight for each member is identified, a fuzzy synthetic process is applied to rank the priorities of alternatives, and we use five steps below to derive the synthetic evaluations. The steps can be described as follows.

Step 1: Aggregate the fuzzy decision matrix of members.

The fuzzy decision matrixes of members are aggregated by using fuzzy arithmetic operations in Ref. [19].

$$\tilde{X} = \begin{array}{c|cccc} & p_1 & p_2 & \cdots & p_n \\ \hline a_1 & \tilde{x}_{11}(c_1) \oplus \cdots \oplus \tilde{x}_{11}(c_n) & \tilde{x}_{12}(c_1) \oplus \cdots \oplus \tilde{x}_{12}(c_n) & \cdots & \tilde{x}_{1n}(c_1) \oplus \cdots \oplus \tilde{x}_{1n}(c_n) \\ a_2 & \tilde{x}_{21}(c_1) \oplus \cdots \oplus \tilde{x}_{21}(c_n) & \tilde{x}_{22}(c_1) \oplus \cdots \oplus \tilde{x}_{22}(c_n) & \cdots & \tilde{x}_{2n}(c_1) \oplus \cdots \oplus \tilde{x}_{2n}(c_n) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_m & \tilde{x}_{m1}(c_1) \oplus \cdots \oplus \tilde{x}_{m1}(c_n) & \tilde{x}_{m2}(c_1) \oplus \cdots \oplus \tilde{x}_{m2}(c_n) & \cdots & \tilde{x}_{mn}(c_1) \oplus \cdots \oplus \tilde{x}_{mn}(c_n) \end{array} \quad (4)$$

Step 2: Normalize the aggregated fuzzy decision matrix.

The raw data are normalized to eliminate anomalies with different measurement units and scales in several MADM problems. However, the purpose of linear scales transform normalization function used in this study is to preserve the property that the ranges of normalized triangular fuzzy numbers are included in [0, 1]. If $\tilde{R}$ denotes the normalized fuzzy decision matrix from $\tilde{X}$, then

$$\tilde{R} = [\tilde{r}_{ij}]_{m\times n}, \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \tag{5}$$

where $\tilde{r}_{ij} = \left(\underline{a}_{ij}, a_{ij}, \bar{a}_{ij}\right)$, then the normalized values are calculated as follows:

$$\tilde{r}_{ij} = \left(\frac{\underline{a}_{ij}}{u_j^+}, \frac{a_{ij}}{u_j^+}, \frac{\bar{a}_{ij}}{u_j^+}\right) \tag{6}$$

where $u_j^+ = \max_i \bar{a}_{ij}$. The normalization method above is to preserve the property that the ranges of normalized triangular fuzzy numbers are belonging to [0, 1].

Step 3: Determine the fuzzy positive ideal and negative ideal solutions.

Because the positive triangular fuzzy numbers are included in the interval [0, 1], the fuzzy positive ideal reference point (FPIRP) denoted by A^+ and fuzzy negative ideal reference point (FNIRP) denoted by A^- can be defined as

$$\begin{cases} A^+ = \left(\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_j^+\right) \\ A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_j^-\right) \end{cases}, \quad j = 1, 2, \ldots, n \tag{7}$$

$$\begin{cases} v_j^+ = (\max_i \tilde{r}_{ij} \,|i = 1, 2, \ldots, m), & j \in B \\ v_j^+ = (\min_i \tilde{r}_{ij} \,|i = 1, 2, \ldots, m), & j \in C \end{cases} \quad \begin{cases} v_j^- = (\min_i \tilde{r}_{ij} \,|i = 1, 2, \ldots, m), & j \in B \\ v_j^- = (\max_i \tilde{r}_{ij} \,|i = 1, 2, \ldots, m), & j \in C \end{cases}$$

where $v_j^+ = (1,1,1)$, $j \in B$; $v_j^+ = (0,0,0)$, $j \in C$ and $v_j^- = (0,0,0)$, $j \in B$; $v_j^- = (1,1,1)$, $j \in C$.

Step 4: Calculate the distances of each initial alternative to FPIRP and FNIRP.

First, the normalized Euclidean distance between two triangular fuzzy numbers must be defined. If $\tilde{A} = (\underline{a}, a, \bar{a})$ and $\tilde{B} = \left(\underline{b}, b, \bar{b}\right)$ are two TFNs, then the normalized Euclidean distance between $\tilde{A}$ and $\tilde{B}$ can be calculated as

$$d\left(\tilde{A}, \tilde{B}\right) = \sqrt{\left[(\underline{a} - \underline{b})^2 + (a - b)^2 + \left(\bar{a} - \bar{b}\right)^2\right]} \tag{8}$$

The distance of alternative between fuzzy positive ideal reference point and fuzzy negative ideal reference point are defined by square distance by using the normalized Euclidean distance:

$$\begin{cases} d_i^+ = \sum_{j=1}^{n} d\left(\tilde{r}_{ij}, \tilde{v}_j^+\right) \\ d_i^- = \sum_{j=1}^{n} d\left(\tilde{r}_{ij}, \tilde{v}_j^-\right) \end{cases}, \quad i = 1, 2, \ldots, m \tag{9}$$

where $d\left(\tilde{r}_{ij}, \tilde{v}_j^+\right)$ denotes the distance between two fuzzy numbers and is calculated by Equation (8). d_i^+ represents the distance from alternative a_i to FPIRP and d_i^- is the distance from alternative a_i to FNIRP.

Step 5: Obtain the closeness coefficient of the alternatives.

Calculate the closeness coefficient (CC_i) of each alternative as

$$CC_i\left(a_i, A^-, A^+\right) = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1, 2, \ldots, m \tag{10}$$

Since $d_i^- \geq 0$ and $d_i^+ \geq 0$, then clearly $CC_i \in [0, 1]$. An alternative with CC_i approaching 1 indicates that the alternative is close to the fuzzy positive ideal reference point and far from the fuzzy negative ideal reference point. The alternative in closeness coefficient matrix with the highest CC_i value will be the best choice.

3. **Experiments.** In this section, there are four experiments to investigate the advantages and effectiveness of the FQSS_GU. First, it has been demonstrated by an illustrative example that FQSS_GU is practical and effective. Then, FQSS_GU and the existing fuzzy TOPSIS [21] are compared for simple user. Next, two approaches above are compared for multiple users. Finally, we analyze the relationship between the time complexities of FQSS_GU with service consumers and alternatives.

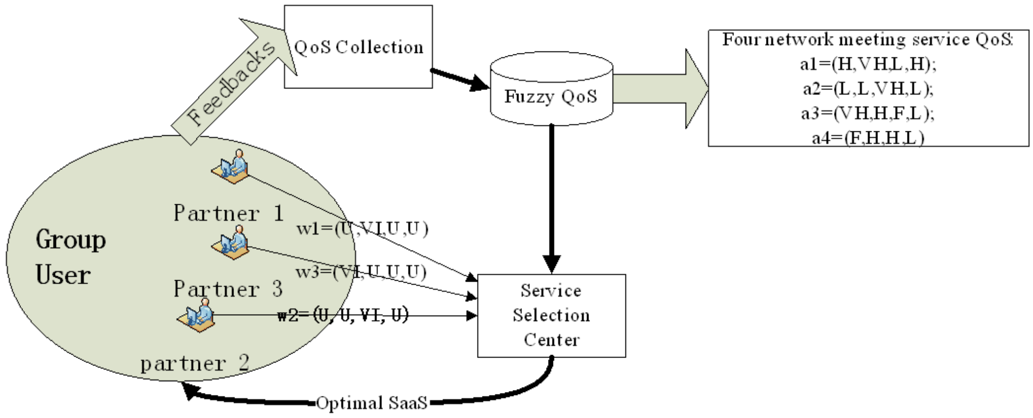

FIGURE 2. Network meeting sample

3.1. **An illustrative example.** A practical example of selecting services is used to illustrate the application of the proposed method in this paper (shown in Figure 2). There are four alternative services for network meeting a_i $(i = 1, 2, 3, 4)$, where the alternative will be evaluated with four QoS criteria with regard to: (1) cost (p_1) is the spending when the client requests the invocation; (2) availability (p_2) is the probability that the service is accessible from user feedback; (3) reliability (p_3) is the probability that a request is correctly responded within the maximum expected time frame from the user's feedbacks; (4) reputation (p_4) is a measure of its trustworthiness from users' feedbacks. Obviously, p_1 is a cost criterion while p_2, p_3 and p_4 are benefit criteria. The QoS values of four alternatives collected by QoS monitor module from users' feedback, with respect to four criteria, are represented by TFNs (shown in Table 3). There are three members in group c_k $(k = 1, 2, 3)$. The QoS preferences $\omega = (\omega_1, \omega_2, \omega_3)$ are shown in Table 4 from users' request, which are personalized. The group weight of fuzzy term is (Very important (VI), Medium (M), Very unimportant (VU)) for (c_1, c_2, c_3), and the TFNs is ((7,9,10),(3,5,7),(1,3,5)), which is assigned by the leader of group. In addition, service customers may put forward their own QoS constraints $(p_1 \leq Fire(F))$, so alternatives must be satisfied the QoS constraints of service customers firstly. And then the decision maker has to perform an evaluation of alternatives and select the best one. The proposed method is applied to solve this problem above according to the following six steps.

Step 1: Construct the fuzzy decision matrix using Equation (1), Equation (2) and Equation (3) shown in Table 5.

Step 2: Aggregate the fuzzy decision matrix of service consumers using Equation (4) shown in Table 6.

Step 3: Normalize the aggregated fuzzy decision matrixes using Equation (5), Equation (6) shown in Table 7.

Step 4: Determine the fuzzy positive ideal and negative ideal solutions A^+ and A^- using Equation (7).

$$A^+ = ((0,0,0), (1,1,1), (1,1,1), (1,1,1))$$
$$A^- = ((1,1,1), (0,0,0), (0,0,0), (0,0,0))$$

Step 5: Calculate the distances of each initial alternative to FPIRP and FNIRP using Equation (9), respectively.

Step 6: Obtain the closeness coefficient of the alternatives using Equation (10).

The distances, closeness coefficient and ranking order of four alternatives are tabulated in Table 8. We can see that the ranking order is "$a_1 \succ a_2 \succ a_4 \succ a_3$", where "$\succ$" indicates the relation "preferred to".

To illustrate our approach can get the alternative with group optimal QoS, we introduce a scoring method to get the optimal alternative. While the group weight is not considered, the ranking orders for members (c_1, c_2, c_3) are "$a_1 \succ a_4 \succ a_2 \succ a_3$", "$a_4 \succ a_2 \succ a_1 \succ a_3$", "$a_4 \succ a_1 = a_2 \succ a_3$", respectively. The best alternative is scored 4 point; the second

TABLE 3. The QoS value of alternative services

	p_1		p_2		p_3		p_4	
	Fuzzy terms	TFNs	Fuzzy terms	TFNs	Fuzzy terms	TFNs	Fuzzy terms	TFNs
a_1	H	(5,7,9)	VH	(7,9,10)	L	(1,3,5)	H	(5,7,9)
a_2	L	(1,3,5)	L	(1,3,5)	VH	(7,9,10)	L	(1,3,5)
a_3	VH	(7,9,10)	H	(5,7,9)	F	(3,5,7)	L	(1,3,5)
a_4	F	(3,5,7)	H	(5,7,9)	H	(5,7,9)	L	(1,3,5)

TABLE 4. The QoS preferences of members ω_k

	p_1		p_2		p_3		p_4	
	Fuzzy terms	TFNs	Fuzzy terms	TFNs	Fuzzy terms	TFNs	Fuzzy terms	TFNs
ω_1	U	(1,3,5)	VI	(7,9,10)	U	(1,3,5)	U	(1,3,5)
ω_2	U	(1,3,5)	U	(1,3,5)	VI	(7,9,10)	U	(1,3,5)
ω_3	VI	(7,9,10)	U	(1,3,5)	U	(1,3,5)	U	(1,3,5)

TABLE 5. The fuzzy decision matrix for members

	p_1	p_2	p_3	p_4
member c_1				
a_1	(35.0,189.0,450.0)	(343.0,729.0,1000.0)	(7.0,81.0,250.0)	(35.0,189.0,450.0)
a_2	(7.0,81.0,250.0)	(49.0,243.0,500.0)	(49.0,243.0,500.0)	(7.0,81.0,250.0)
a_3	(49.0,243.0,500.0)	(245.0,567.0,900.0)	(21.0,135.0,350.0)	(7.0,81.0,250.0)
a_4	(21.0,135.0,350.0)	(245.0,567.0,900.0)	(35.0,189.0,450.0)	(7.0,81.0,250.0)
member c_2				
a_1	(15.0,105.0,315.0)	(21.0,135.0,350.0)	(21.0,135.0,350.0)	(15.0,105.0,315.0)
a_2	(3.0,45.0,175.0)	(3.0,45.0,175.0)	(147.0,405.0,700.0)	(3.0,45.0,175.0)
a_3	(21.0,135.0,350.0)	(15.0,105.0,315.0)	(63.0,225.0,490.0)	(3.0,45.0,175.0)
a_4	(9.0,75.0,245.0)	(15.0,105.0,315.0)	(105.0,315.0,630.0)	(3.0,45.0,175.0)
member c_3				
a_1	(35.0,189.0,450.0)	(7.0,81.0,250.0)	(1.0,27.0,125.0)	(5.0,63.0,225.0)
a_2	(7.0,81.0,250.0)	(1.0,27.0,125.0)	(7.0,81.0,250.0)	(1.0,27.0,125.0)
a_3	(49.0,243.0,500.0)	(5.0,63.0,225.0)	(3.0,45.0,175.0)	(1.0,27.0,125.0)
a_4	(21.0,135.0,350.0)	(5.0,63.0,225.0)	(5.0,63.0,225.0)	(1.0,27.0,125.0)

TABLE 6. The aggregated fuzzy decision matrix for members

	p_1	p_2	p_3	p_4
a_1	(85.0,483.0,1215.0)	(371.0,945.0,1600.0)	(29.0,243.0,725.0)	(55.0,357.0,990.0)
a_2	(17.0,207.0,675.0)	(53.0,315.0,800.0)	(203.0,729.0,1450.0)	(11.0,153.0,550.0)
a_3	(119.0,621.0,1350.0)	(265.0,735.0,1440.0)	(87.0,405.0,1015.0)	(11.0,153.0,550.0)
a_4	(51.0,345.0,945.0)	(265.0,735.0,1440.0)	(145.0,567.0,1305.0)	(11.0,153.0,550.0)

TABLE 7. The normalized fuzzy decision matrix

	p_1	p_2	p_3	p_4
a_1	(0.063,0.3578,0.9)	(0.2319,0.5906,1.0)	(0.02,0.1676,0.5)	(0.0556,0.3606,1.0)
a_2	(0.0126,0.1533,0.5)	(0.0331,0.1969,0.5)	(0.14,0.5028,1.0)	(0.0111,0.1545,0.5556)
a_3	(0.0881,0.46,1.0)	(0.1656,0.4594,0.9)	(0.06,0.2793,0.7)	(0.0111,0.1545,0.5556)
a_4	(0.0378,0.2556,0.7)	(0.1656,0.4594,0.9)	(0.1,0.391,0.9)	(0.0111,0.1545,0.5556)

TABLE 8. Distances, closeness coefficient and ranking order of four alternatives

	$d(a_i, A^+)$	$d(a_i, A^-)$	CC_i	Rank
a_1	2.5179	2.2614	0.4732	2
a_2	2.4503	2.0996	0.4615	3
a_3	2.7137	1.9726	0.4209	4
a_4	2.4315	2.2171	0.4769	1

TABLE 9. The QoS value of alternatives for comparison

	p_1		p_2		p_3		p_4	
	Fuzzy terms	TFNs	Fuzzy terms	TFNs	Fuzzy terms	TFNs	Fuzzy terms	TFNs
a_1	VH	(7,9,10)	VH	(7,9,10)	L	(1,3,5)	L	(1,3,5)
a_2	VH	(7,9,10)	L	(1,3,5)	VH	(7,9,10)	L	(1,3,5)
a_3	VH	(7,9,10)	L	(1,3,5)	L	(1,3,5)	L	(1,3,5)
a_4	L	(1,3,5)	L	(1,3,5)	L	(1,3,5)	L	(1,3,5)

alternative is scored 3 and so on. Therefore, the scorings of alternatives (a_1, a_2, a_3, a_4) for three members (c_1, c_2, c_3) are "(4, 2, 1, 3)", "(2, 3, 1, 4)", "(3, 3, 1, 4)", respectively. The most important member is scored 3 in group; the second member is scored 2 and so on. So, the scorings of members (c_1, c_2, c_3) in group is "(3, 2, 1)". The synthetic scorings of alternatives (a_1, a_2, a_3, a_4) for three members (c_1, c_2, c_3) are "(12, 6, 3, 9)", "(4, 6, 2, 8)", "(3, 3, 1, 4)", respectively. The total scorings of alternatives (a_1, a_2, a_3, a_4) is "(19, 15, 6, 21)", the ranking order is $a_4 \succ a_1 \succ a_2 \succ a_3$. The result is same with the proposed approach in this paper, so our approach is feasible.

3.2. **The comparison for simple user.** The existing fuzzy TOPSIS (named FTOPSIS) method was proposed in Ref. [21], which was applied in evaluating transportation service quality [22,23]. In this section, it will be proved by several experiments that our approach is superior to the FTOPSIS (only one member is considered in group, and the member's three QoS preferences are shown in Table 4). In order to clearly illustrate the advantages of our algorithm, a group of extreme alternatives is provided in Table 9.

When $\omega_3 = ((7, 9, 10), (1, 3, 5), (1, 3, 5), (1, 3, 5))$, the ranking orders by our approach is $a_4 \succ a_1 = a_2 \succ a_3$; while the ranking orders is $a_1 \succ a_2 \succ a_3 \succ a_4$ by FTOPSIS. It is obviously that a_4 is the optimal solution shown in Table 9. Therefore, our approach is superior to the FTOPSIS. In addition, the time complexity of FQSS_GU is $O(m \times n \times q + 5 \times m \times n)$ and the time complexity of FTOPSIS is $O(m \times n \times q + 8 \times m \times n)$, so the order of magnitude of time complexity of the two methods is the same and FQSS_GU is slightly better than FTOPSIS.

3.3. **The comparison for multiple users.** FTOPSIS can evaluate alternatives, but it only supports one user. To accurately describe FQSS_GU is superior to FTOPSIS, we define a method to compute the close degree of group optimal plan by FTOPSIS as follows:

$$CC_{FTOPSIS} = \frac{\sum_{k=1}^{g} CC_k \left(a_k, A^-, A^+\right)}{g} \tag{11}$$

where a_k is the optimal plan for user k, A^-, A^+ are the fuzzy positive ideal and the fuzzy negative ideal solutions, g denotes the number of users, CC_k is the close degree of a_k, $CC_{FTOPSIS}$ is the average close degree of $a_1, \ldots, a_k$. The candidate plans and users' weights are randomly generated, and the value is got from Table 1 and Table 2. To obtain more possibility, the weight of users and QoS are generated. The experiment was performed 100 times, we get the average close degrees.

First, we compare the FQSS_GU and FTOPSIS when the number of users is fixed. Figure 3 shows the experimental results in the case of three users evaluating candidate plans. Obviously, FQSS_GU is superior to FTOPSIS. The reason is that FQSS_GU has considered the all users evaluation of candidate plans while FTOPSIS has considered only

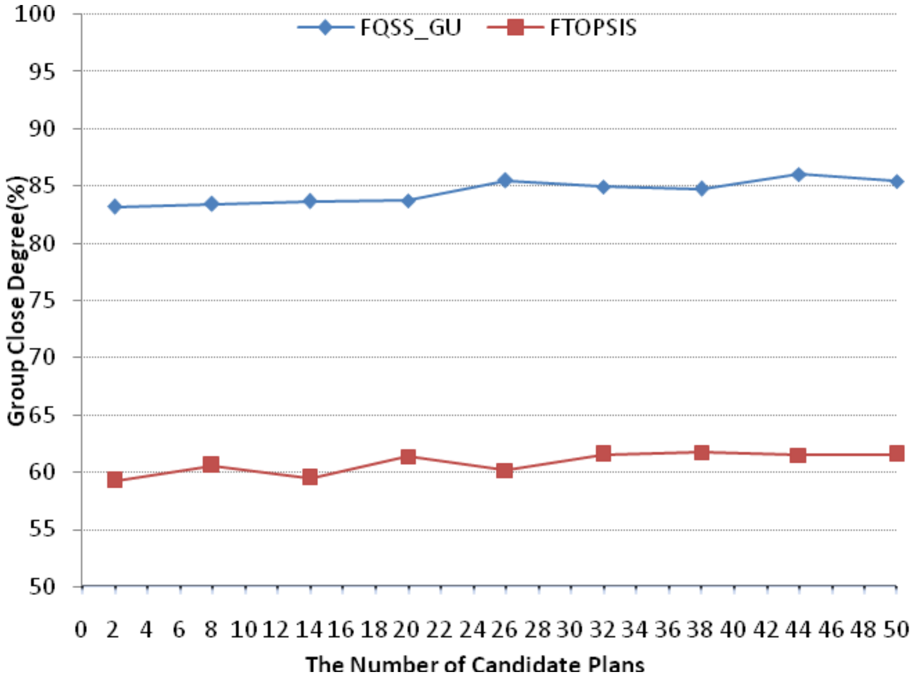

Figure 3. Comparison of two algorithms
(Relation between close degree and the number of candidate plans)

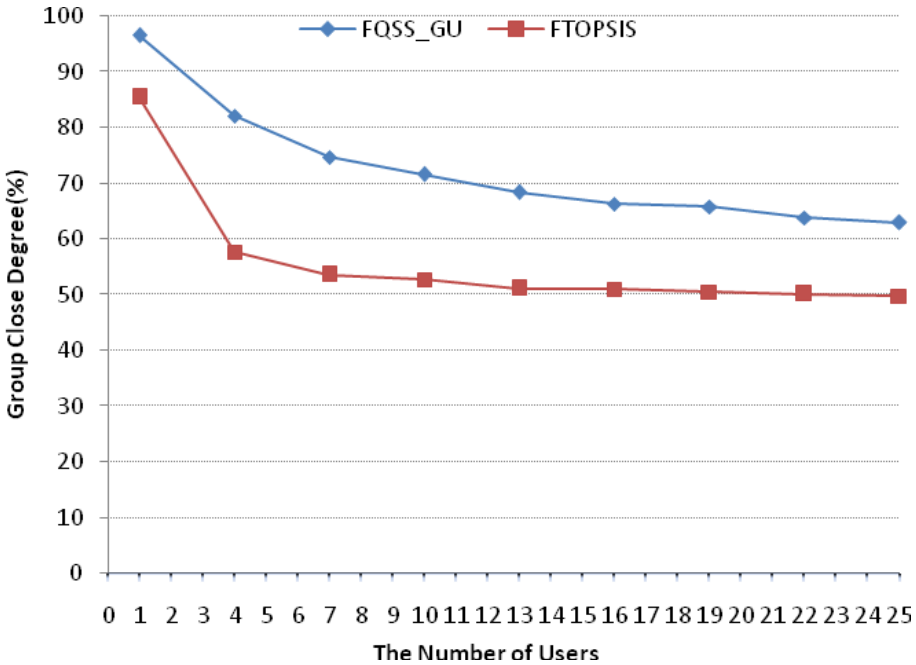

Figure 4. Comparison of two algorithms
(Relation between close degree and the number of decision makers)

certain users evaluations of candidate plans. With the number of candidates increasing, the close degrees of optimal solution of two kinds of algorithms increase.

Similarly, we compare the FQSS_GU and FTOPSIS when the number of alternatives is fixed. Figure 4 shows the experimental results when the number of candidate plans is 25. Obviously, FQSS_GU is superior to FTOPSIS. With the number of users increasing, the close degrees of optimal solution of two kinds of algorithms reduce and FQSS_GU is

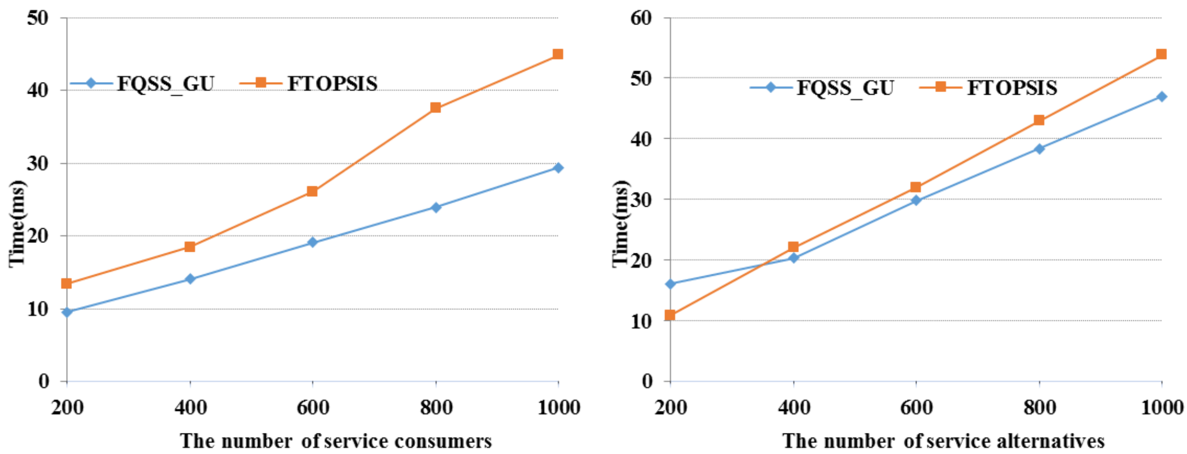

FIGURE 5. Time complexity

faster than the FTOPSIS. However, with the number of users increasing, the close degree of the optimal plan obtained by FQSS_GU is close to FTOPSIS, but is always higher than FTOPSIS.

3.4. **Time complexity analysis.** Two experiments aimed at comparing the time complexity of two selection approaches previously described (FQSS_GU, FTOPSIS). The experiments are conducted on a Pentium computer with a 2.0 GHz CPU and 2 GB RAM. These experiments are: 1) analyze the relationship between the computation time and the number of members in group.

Suppose the number of alternatives is 100, and the number of member changes from 200 to 1000. The case is executed 100 times, then we get the average time. 2) Analyze the relationship between computation time and the number of alternative. Suppose the number of member is 100, and the number of service alternatives changes from 200 to 1000. The case is executed 100 times, then we get the average time. The results of experiments are shown in Figure 5, which demonstrates FQSS_GU is superior to the existing FTOPSIS and it has linear time complexity.

4. **Related Work.** Service selection and rating is a research topic that emerged recently with the advent of SOA and SaaS. Few works in this area have addressed different facets of the topic, such as the model of QoS, the assessment of QoS at selection time, and the measurement of QoS at execution time.

For example, [3,4] proposed a hybrid QoS ontology supporting real numbers, interval numbers and triangular fuzzy numbers. P. Wang proposed a fuzzy QoS criterion description method with Intuitionistic fuzzy set [5]. Based on works [3-5], L. Zhang et al. proposed an extensible hybrid QoS model supporting above four data types [6]. A novel approach for designing and developing a QoS ontology was presented in Ref. [7], which can support not only describing QoS information in great detail but also facilitating various service participants in expressing their QoS offers and demands at different levels of expectation.

Based on the QoS performance of services, various approaches have been proposed for service selection. We divide the existing service selection approaches into three categories. The first category is collaborative filtering recommendation. An effective personalized collaborative filtering method for Web service recommendation was proposed in Ref. [8], which took into account the personalized influence of services when computing similarity measurement between users and personalized influence of services. A method of location-aware collaborative filtering to recommend Web services to users by incorporating locations of both users and services was proposed in Ref. [9]. A collaborative filtering approach was proposed for predicting QoS values of Web services and making Web service recommendation in Ref. [10,24]. The second category is linear programming. Based on TOPSIS, [3,4] proposed a hybrid TOPSIS method for QoS model with hybrid data types. P. Wang proposed an extended Max-Min-Max method for service selection for QoS criterion expressed by intuitionistic fuzzy sets [5]. Based on TOPSIS, P. Wang et al. [2] proposed a service selection method to supporting triangular fuzzy numbers. As well as, AHP [7,11] and Markov decision process [8] were applied in service selection. Anselmi et al. [12] provided a Mixed Integer Linear Programming (MILP) based on formulation of the selection problem and considered a greedy heuristic to find near-optimal solutions. Service selection problem was formalized as a Mixed Integer Linear Programming problem, loops peeling was adopted in the optimization, and constraints posed by stateful Web services were considered in Ref. [13]. Thirdly, heuristics. Considering the complexity of Integer Linear Programming optimization, Yu et al. [14] proposed heuristics to find near-optimal solutions in polynomial time. Researchers discussed the feasibility of genetic algorithm, ant colony optimization and particle swarm being applied in service selection in Ref. [15-18,25].

However, the above methods were all based on single-user or multi-users with the same QoS requirements. Obviously, they ignored the service selection for multi-users (group user) with personalized QoS requirements and the expression habits of users. Compared with the above methods, our method has the following advantages: 1) FQSS_GU can obtain group optimal service; 2) FQSS_GU can support the QoS and users QoS preferences expressed by fuzzy terms; 3) FQSS_GU is a general algorithm for single-user and group user.

5. **Conclusions.**

Group activities exist in everywhere of social life, and it is the trend that provides information service based on user personalized QoS requirement. In this perspective, we have presented a fuzzy QoS-driven service selection method based on multiple attribute decision making theory for group user-FQSS_GU, which supports the user feedback information and requirement information expressed by fuzzy terms. FQSS_GU is a general service selection method for single user and group user, which can gain the optimal service for single use and gain group optimal service for group. Our method provides a practical and effective solution for the group-oriented service selection.

Our future work includes up improving FQSS_GU performance. Lots of alterative services and more members in group will affect the user experience of FQSS_GU. Further, it is reasonable that as some QoS attributes of service expressed by interval numbers, we will propose a service selection method based on interval numbers for group user.

Acknowledgment. The authors are very grateful to the anonymous referees for their insightful and constructive comments and suggestions that have led to an improved version of this paper. This work is supported by the MOE (Ministry of Education in China) Project of Humanities and Social Sciences (Project No. 12YJC870030); the Liaoning Province in China Project of Social Sciences Planning Fund (Project No. L12CTQ008); the Science and Technology Project of Hunan Province in China (Project No. 2013NK30 25); the Teaching Reform Project of Hunan Institute of Technology (Project No. A1332); the Bachelor Degree in Construction Project of Hunan Institute of Technology (Project No. H1321).

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