# HANDLING UNCERTAINTY DURING SERVICES RANKING

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## Abstract

Many researchers have suggested fuzzy-based methods to derive rankings of services based on the fuzzy degree that each service satisfies a set of weighted quality attributes. Most of these methods assume a closed set of candidate services completely assessed. However, the candidate service set may include services which have not been fully assessed yet with respect to all quality attributes. Unassessed candidates introduce hesitation regarding the ranking of already evaluated services. In addition, even after services have been completely assessed, users may challenge the alleged assessments by disagreeing with them. Furthermore, users may suggest their preferences for quality attributes of services without providing numbers or ranges of numbers, but rather by providing characterizations of the relative importance of each attribute for their specific purposes. This paper suggests Intuitionistic Fuzzy Sets (IFSs) to handle these sources of uncertainty during services' ranking based on their Quality of Service (QoS) attributes. IFS score functions are used to rank services with regard to each quality attribute. The final ranking can be derived by applying an objective method based on entropy weights for the quality attributes. In addition, users' subjective selection of services based on preferences for the relative importance of quality properties is also discussed.

**Keywords:** Intuitionistic Fuzzy Sets, Software quality, Web services, Services ranking

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## 1. INTRODUCTION

The problem addressed in this paper is ranking of web services when assessment of their quality of service (QoS) attributes is characterized by uncertainty. Consider, for example, a broker evaluating services. The broker may have evaluated a subset of candidate services (already present in the service registry) which provide a similar function. Thus, the evaluator's assessment horizon includes a number of services, but not all of them have been fully evaluated on their quality attributes. Even if all candidate services have been assessed, a new service may appear in the evaluator's horizon also providing the same function. Most objective ranking methods cannot handle these sources of hesitation, since they often assume a closed set of completely assessed services (Al-Masri and Mahmoud, 2007, Xiong and Fan, 2007). In addition, users of services may agree or disagree with the provided assessments regarding the quality properties of services as advertised by the service brokers. To allow service quality assessments to be as reliable as possible, despite unassessed candidate services, and also in order to consider in the process users' opinions and preferences, we introduce a service ranking approach based on Intuitionistic Fuzzy Sets (IFSs) (Atanassov, 1986). In particular, we describe an approach for mapping quantitative quality attribute assessments to IFSs and then we discuss how this mapping can be useful to indicate rankings of candidate services with regard to quality attributes. Ranking can take place before all candidate services have been assessed fully and after all candidate services have been assessed and used. IFS scores and accuracy functions are used to derive service rankings with regard to each attribute. We also present how we can derive the final ranking of services with respect to all quality attributes by applying an objective method (Ye, 2010) based on entropy weights. Furthermore, users can also express subjective preferences for specific quality properties of services when looking for a suitable service. These preferences can be mapped to Intuitionistic Fuzzy Numbers (IFNs) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) can be used subsequently to provide a user-specific ranking of all the services in a category.

The contributions of this work are mainly the following: (a) It handles uncertainty stemming from broker service providers who perform their own objective evaluations and occasionally have incomplete values for some QoS attributes due to currently unassessed services and services' QoS attributes. (b) It addresses uncertainty stemming from missing subjective weights about QoS attributes using objective (entropy) weights. (c) It considers uncertainty on whether the measurement presented by the broker as maximum (minimum) in a benefit (cost) attribute is satisfying for the user whereas at the same time also considers users' preferences for specific QoS attributes. (d) It places all the above in a comprehensive framework for services' ranking and selection that handles various sources of uncertainty both for services' brokers and users using IFSs.

The remainder of the paper is structured as follows. In the following Section 2 we discuss related work. In Section 3, we describe the proposed approach for mapping of quality attribute assessments to IFSs in face of partially completed assessments and in Section 4, we provide a simple example that exemplifies the mapping approach. In Section 5, we demonstrate how service ranking is performed. In Section 6, we discuss adjusting service quality assessment based on users' opinions about the advertised values of quality attributes and show how quality assessments and objective ranking may be rearranged in this case using a fully assessed real set of fax services. In Section 7, we present how user-specific subjective ranking of services can take place based on user preferences and with the use of TOPSIS method. Finally, in Section 8, we conclude the paper and discuss some future research directions.

## 2. RELATED WORK

Service ranking techniques are broadly classified into objective, subjective or hybrid (Almulla et al., 2015), according to the paradigm they follow to determine attribute weights. Objective methods are suitable for quantifiable attributes (Qu et al., 2014) and determine attribute weights directly from existing data and quality measurements, relying on quality attribute values provided by service providers or trusted service brokers (Choi and Jeong, 2014). These values can be stored in the UDDI (Universal Description, Discovery, and Integration) registry, since the UDDI registry has the capability for storing quality information using the tModels feature (Patil and Gopal, 2010). Subjective techniques specify attribute weights based on preferences given by users, providers or domain experts and they are appropriate in case of unquantifiable qualitative attributes. Hybrid techniques (Almulla et al., 2015) are also proposed to determine synthetic weights for attributes by combining available objective information and experts' preferences.

In all cases, ranking of services can be affected by certain sources of uncertainty which have been classified as (Platenius et al., 2013): (a) uncertainty due to incomplete knowledge caused by partial service assessments provided by the service provider or by the broker, (b) uncertainty due the assumptions adopted for services' evaluation by the applied ranking technique, and (c) uncertainty due to users' vague preferences on services' QoS attributes and also users' uncertainty on the suitability of the evaluated max and min values of benefit and cost quality attributes. Our approach handles these sources of uncertainty with Intuitionistic Fuzzy Sets (IFSs), as follows: (a) We use IFSs to reflect missing evaluations of services by the broker. (b) When we have unknown information on QoS criteria weights, we calculate entropy (i.e. objective) weights to conclude at a final objective ranking of web services. (c) We use IFSs reflecting the users' agreement or disagreement on the evaluated max and min values of benefit and cost quality attributes, respectively. We also use IFSs to represent users' preferences on the importance of QoS attributes, instead of users' preferences on the ranges of QoS attributes' values. This makes it more practical for users to specify their requests.

In the following we discuss representative approaches with respect to the previously mentioned sources of uncertainty and compare them with the suggested approach in this work.

### 2.1 Uncertainty due to partial service assessments

In the literature, a number of works (e.g. (Shao et al., 2007), (Zheng et al., 2011), (Ding et al., 2014a), (Ding et al., 2014b)) address the problem of services' evaluation in the presence of missing values for some QoS attributes. Most of these approaches perform ranking prediction based on multiple users' subjective perceptions or observations for QoS values and apply collaborative filtering techniques. They solve the problem of predicting missing QoS values of a service by calculating the similarity to other neighboring services. Our work is predominately oriented towards broker service providers who perform their own objective evaluations and occasionally have incomplete values for some QoS attributes. The broker does not have any users' assessments for the same QoS value in multiple services and therefore prediction is not relevant. Unknown values are related to partially evaluated services by the broker and introduce uncertainty in the evaluation of the broker which is managed with the use of IFSs.

In (Platenius et al., 2015) incomplete characterization of services is also considered with the aim to determine the extent to which partially complete service specifications for QoS attributes match users' requirements. In this approach, a fuzziness service score is computed, however this is from the users' perspective on the importance of each service QoS attribute combining also incomplete assessments. In our work we adopt a brokers' perspective in which users' preferences are utilized as weights which are applied to services' QoS characterizations in terms of IFSs already reflecting the uncertainty of the broker due to missing QoS values.

### 2.2 Uncertainty due to services' evaluation and ranking techniques

When applying a subjective ranking technique, a critical issue is the determination of QoS attributes' weights. This problem has a profound effect in the final ranking of services. There are some powerful hybrid techniques which try to address this issue. For example, in (Almulla et al., 2015) decision makers (domain experts) are asked to provide both importance weights of QoS attributes and acceptable ranges of values for these attributes. These ratings are used to calculate subjective weights. Objective QoS attributes' weights may also be computed by considering dependencies among attributes based on correlation metrics between attributes. Finally, synthetic weights are calculated by combining the subjective and objective weights.

Similarly, our approach takes into account that information about attribute weights may be completely unknown. In such a case, we can derive objective (entropy) attribute weights by adopting a method which is suitable when attribute values take the form of intuitionistic fuzzy numbers (Ye, 2010). This method is applied to calculate correlation of each service's attributes with the attributes of a hypothetical ideal service, that is the service satisfying all attributes at the maximum degree.

### 2.3 Uncertainty of users' preferences

Regarding uncertainty due to vague users' preferences there are many subjective fuzzy-based approaches in the literature (e.g., (Xiong and Fan, 2007, Almulla et al., 2015, Qu et al., 2014, Fletcher et al., 2015)). Fuzzy-based techniques aim to rank services based on the fuzzy degree that each alternative service satisfies a set of weighted quality attributes. These techniques handle uncertain ratings of service quality attributes, imprecise preferences for attribute weights and vague relationships/trade-offs among quality attributes. One interesting approach was presented recently in (Fletcher et al., 2015) and uses fuzzy logic to represent both importance of QoS attributes' weights according to users and also their trade-offs. Our work considers users' preferences as well and similarly to (Fletcher et al., 2015) we do not assume that users provide required ranges for QoS attributes' values. In (Fletcher et al., 2015) the authors also consider trade-offs, but they assume that all QoS attributes are fully measured, whereas our approach makes no such assumption.

There are also some subjective ranking approaches which adopt fuzzy set generalizations, such as IFSs/vague sets (Wang, 2009, Wang, 2013), to represent imprecise perceptions and hesitation of users and decision makers regarding service quality attributes. In our approach it is not necessary to ask decision makers' perceptions on QoS attribute characterizations, since the broker service is assumed to be responsible for providing concrete measurements at least for the quantifiable QoS attributes. Similarly to these approaches, we also map users' preferences for QoS attributes' weights to IFSs. Differently from these approaches, we also consider users' uncertainty on whether the measurement presented by the broker as maximum (minimum) in a benefit (cost) attribute is satisfying.

Multi-criteria decision making techniques are among the most popular for service subjective selection and ranking. The two most widely used approaches in the literature are AHP (Choi C. R. and Jeong, 2014) and TOPSIS (Whaiduzzaman et al., 2014). As the number of QoS attributes grows, AHP becomes ineffective due to the use of pairwise comparisons among the attributes. On the contrary TOPSIS, and especially TOPSIS based on fuzzy sets, is quite efficient and reduces the complexity of the decision making process (Whaiduzzaman et al., 2014). In particular, the fuzzy-based TOPSIS approach is very suitable for cases where both cost and benefit attributes are used. For these reasons, in this work we apply a fuzzy-based TOPSIS technique inspired by the one introduced in (Boran et al., 2009) for the subjective ranking of services (described in Section 7).

# 3. MAPPING QUALITY ASSESSMENTS TO IFSS

An Intuitionistic Fuzzy Set (IFS) $A$ in a finite set $X$ is defined as (Atanassov, 1986):

$$A = \{< x, \mu_A(x), u_A(x), \pi_A(x) > | x \in X\} \qquad □□□$$

Where $: \mu_A: X \to [0,1]$ , $u_A: X \to [0,1]$ , $0 \leq \mu_A(x) + u_A(x) \leq 1$ and $\pi_A(x) = 1 - \mu_A(x) - u_A(x)\ \forall x \in X$ . Functions $\mu_A(x)$ and $u_A(x)$ denote, respectively, the degree of membership and the degree of non-membership of $x$ to $A$. $\pi_A(x)$ is the hesitation degree of whether $x$ belongs to $A$.

We assume a list of $N$ services $S = \{S_1, S_2, \ldots, S_N\}$ matching a requested functionality and a list of $K$ quantitative quality attributes $Q = \{Q_1, Q_2, \ldots, Q_K\}$ used to compare the services. In the following, we provide IFS-based semantics for the membership, non-membership and hesitation of the level that service $S_i$ satisfies attribute $Q_k$.

Initially, before any evaluation, hesitation for the level that service $S_i$ satisfies attribute $Q_k$ is maximal (equal to 1):

$$\{< S_i, \mu = 0, u = 0, \pi = 1 > | \forall i \in 1 \ldots N\}, \quad \forall k \in 1 \ldots K \tag{2}$$

Now assume that we have used an evaluation function $F_k(S_i)$ that returns the value of $Q_k$ attribute for service $S_i$ . The attribute set $Q$ is divided into the subset $Q^1$ of benefit attributes and the subset $Q^2$ of cost attributes. For a benefit (cost) attribute, such as availability (response time), the higher (lower) its value, the better the service quality is (Fletcher et al., 2015) Given that we have assessed all attributes of each alternative service in relation to the rest, we can eliminate hesitation in our evaluations. Let $P = \max\{F_k(S_i) | i = \{1..N\}\}$ and $p = \min\{F_k(S_i) | i = \{1..N\}\}$ be the maximum and minimum value of alternative services in relation to attribute $Q_k$. The membership for the level that service $S_i$ satisfies attribute $Q_k$ is calculated by equation (3):

$$\mu_k(i) = \begin{cases} \dfrac{F_k(S_i) - p}{P - p}, \forall\ k \in Q^1 \\ \dfrac{P - F_k(S_i)}{P - p}, \forall\ k \in Q^2 \end{cases} \tag{3}$$

In this fully informed state, hesitation is completely eliminated, as shown in equation (4):

$$\{< S_i, \mu = \mu_k(i), u = 1 - \mu_k(i), \pi = 0 > | \ \forall i \in 1 \ldots N, \forall k \in 1 \ldots K\} \tag{4}$$

We have now to consider an aspect of hesitation that prevents the evaluator from reaching this fully informed state. The *evaluator's assessment horizon* may include a number of services but not all of them have been fully evaluated. In addition, a new service may appear anytime that also fulfills the same function. This new service introduces uncertainty to the validity of membership/non-membership parts of satisfaction of quality attributes with respect to (already) evaluated services. To allow assessments to be reliable, in such cases, we introduce a semi-informed state. Let us assume, given $M$ services, we have assessed in relation to attribute $Q_k$ only $L$ services ($L < M$.) We are, therefore, only $\vartheta = L/M < 1$ certain of the membership and non-membership parts of satisfaction of quality attributes with respect to already evaluated services. We call $\vartheta$ as the *horizon uncertainty factor*.

Assessment of the new service, when completed, may change existing service assessments, either towards increasing membership or non-membership. This is because in Eq. 3, membership is affected by the minimum and maximum quality attribute values of the assessed services, and the new service value, which is currently unknown, may cause changes for all the already assessed services. In this semi-informed state, we have to re-calculate the membership, non-membership and hesitation value for the level that service $S_i$ satisfies attribute $Q_k$ by applying equation (5):

$$\big\{< S_i, \mu = \vartheta \times \mu_k(i), u = \vartheta \times (1-\mu_k(i)\big), \pi = 1-\mu-u > | \; \forall i \in 1 \dots N, k \in 1 \dots K\} \quad (5)$$

## 4. A Simple Example

Consider two services $S_1$ and $S_2$ providing the same functionality. We want to compare these two services with regard to attribute $Q_k$ which we assume that is throughput. Initially, we apply the assessment function $F_k$ only to service $S_1$ and let assume that $F_k$ returns a throughput value equal to 5 MBPS (i.e., $F_k(S_1) = 5$). Since we consider only one service ($S_1$), the maximum and minimum throughput values of all assessed services are the same (i.e. $P = p = 5$) and, thus, we assign full membership to the one and only assessed service $S_1$, i.e., $\{< S_1, 1, 0, 0 >\}$. However, since there is one more service that we have not assessed yet ($S_2$), the horizon uncertainty factor is equal to $\vartheta = 1/2 = 0.5$ and this value can be used to derive (by Eq. 5), a new IFS for the assessment of service $S_1$ with respect to attribute $Q_k$ (throughput):
$\{< S_1, 0.5 \times 1, 0.5 \times (1-1), 1-0.5 >\} =$
$\{< S_1, 0.5, 0, 0.5 >\}$

Now assume that we evaluate throughput of service $S_2$ and the result is $F_k(S_2) = 10$ MBPS. We calculate the maximum and minimum throughput of both assessed services ($S_1$ and $S_2$), and we have that $P = 10$ and $p = 5$. The upper part of equation (3) (because throughput is a benefit attribute) yields new membership values for services $S_1$ and $S_2$, equal to $\mu_k(S_1) = (5-5)/(10-5) = 0$ and $\mu_k(S_2) = (10-5)/(10-5) = 1$, respectively. Using Eq. (4), we get: $\{< S_1, 0, 1, 0 >, < S_2, 1, 0, 0 >\}$. The interpretation of this result is rather straightforward. Having only two services and nothing else in the evaluation horizon, this result indicates both the best and the worst choice with regard to attribute $Q_k$. Service $S_1$ is the least attractive service, having a membership of 0, and service $S_2$ is the most attractive service, having a membership of 1. Since, so far, no other alternative services exist in the evaluation horizon, the hesitation part is in both cases 0.

Assume now that a third service $S_3$ appears in the evaluator's horizon (i.e., service $S_3$ is also found that satisfies the requested functionality). Until we have the opportunity to evaluate the attributes of service $S_3$, the mere fact that this service exists as candidate, introduces uncertainty in the suitability of other already assessed services. The horizon uncertainty factor is now equal to $\vartheta = 2/3 = 0.67$ and this value can be used to adjust values of previously computed IFSs until we have the opportunity to evaluate the throughput of service $S_3$. Equation (5) yields the following IFSs:

$$\{< S_1, 0.67 \times 0, 0.67 \times 1, 1-0.67 >, < S_2, 0.67 \times 1, 0.67 \times 0, 1-0.67 >\} = \{< S_1, 0, 0.67, 0.33 >, < S_2, 0.67, 0, 0.33 >\}$$

These IFSs reflect the fact that although service $S_1$ has still zero membership and service $S_2$ has still zero non-membership, we hesitate to assign to them full non-membership and full membership, respectively, due to the existence of service $S_3$, that has not been evaluated yet.

Finally, assume that $F_k(S_3) = 3$ MBPS. We calculate again maximum and minimum throughput of all assessed services (i.e., services $S_1$, $S_2$ and $S_3$) and the results are $P = \max\{5, 10, 3\} = 10$ and $p = \min\{5, 10, 3\} = 3$. Eq. (3) yields the new membership values for services: $\mu_k(S_1) = (5-3)/(10-3) = 0.29$, $\mu_k(S_2) = (10-3)/(10-3) = 1$ and $\mu_k(S_3) = (3-3)/(10-3) = 0$. Service $S_2$ is still the more attractive choice because there is a third worst alternative ($S_3$) which presents now the lowest throughput, whereas service $S_1$ is the second choice. Equation (4) yields the final IFSs:

$$\{< S_1, 0.29, 0.71, 0 >, < S_2, 1, 0, 0 >, < S_3, 0, 1, 0 >\}$$

## 5. Ranking Web Services

In this Section we will first demonstrate how uncertainty due to unknown values related to partially evaluated services is managed in order to derive web services' rankings according to each QoS attribute. In realistic settings of large service data sets, we need a practical mechanism that will facilitate service ranking through calculation of scores. For this purpose, we use score and accuracy functions as they are defined for IFSs.

Let $A =< \mu_A, u_A >$ be an IFS. The IFS score function $\Delta$ of $A$ is equal to (Chen and Tan, 1994): $\Delta(A) = \mu_A - u_A$. Considering membership and non-membership of an IFS (see Eq. (1)), it holds that $\Delta(A) \in [-1,1]$. The IFS score function $\Delta(A)$ represents the "net membership" degree. The accuracy function $\sigma$ of $A$ is equal to (Hong and Choi, 2000): $\sigma(A) = \mu_A + u_A = 1 - \pi_A$. Considering membership and non-membership of an IFS (see Eq. (1)), it holds that $\sigma(A) \in [0,1]$. The IFS accuracy function $\sigma(A)$ represents the "non-hesitation" degree. To rank two IFSs $A =< \mu_A, u_A >$ and $B =< \mu_B, u_B >$, their IFS score and accuracy functions have to be compared as follows (Hong and Choi, 2000): If $\Delta(A) > \Delta(B)$ then A is ranked higher than B. Otherwise, if $\Delta(A) = \Delta(B)$, then the service with a higher accuracy is ranked higher.

We demonstrate how ranking is performed by examining an exemplar set of services that slightly modifies an example presented in (Almulla, 2015). Assume six web services: $S =$

$\{S_1, S_2, \ldots, S_6\}$ providing the same function (Table I). Services are characterized by four quality attributes, $Q_1$: Response Time, $Q_2$: Availability, $Q_3$: Throughput, and $Q_4$: Successability. Response time ($Q_1$) is a cost attribute, while all the rest are benefit attributes. Consider in Table I that we are fully aware for the values of attributes of services $S_1, S_2, S_3$ and $S_4$.

TABLE I: VALUES OF QOS ATTRIBUTES FOR A SAMPLE OF WEB SERVICES

| *Service* | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ |
|---|---|---|---|---|
| $S_1$ | 47.27 | 20 | 24.3 | 25 |
| $S_2$ | 54.8 | 86 | 60.1 | 80 |
| $S_3$ | 61 | 90 | 16 | 76 |
| $S_4$ | 63.83 | 40 | 5.1 | 30 |
| $S_5$ | Unknown | 44 | Unknown | 18 |
| $S_6$ | Unknown | Unknown | Unknown | Unknown |

For service $S_5$, only availability ($Q_2$) and successability ($Q_4$) are known, while, for service $S_6$, we have no assessments yet. Table II presents the results of mapping assessments of service attributes to IFSs.

Table II presents also rankings of services with respect to each attribute. These rankings are calculated by applying the IFS score function and follow a descending order of IFS scores. The following rankings are derived (from the best choice to the worst): $S_1, S_2, S_3, S_4$ (with respect to response time), $S_3, S_2, S_5, S_4, S_1$ (with respect to availability), $S_2, S_1, S_3, S_4$ (with respect to throughput), and $S_4, S_1, S_2, S_3, S_5$ (with respect to successability).

In the following we will discuss how QoS attributes weights can be calculated objectively in case that there is no available information on QoS importance weights.

TABLE II: RANKING OF SERVICES BASED ON VARIOUS QUALITY ATTRIBUTES

| | *Response Time ($Q_1$)* | | | | | | *Throughput ($Q_3$)* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *[μ,u]* | *Δ* | *ϑ* | *Adjusted [μ,u]* | *Δ* | *Rank* | *[μ,u]* | *Δ* | *ϑ* | *Adjusted [μ,u]* | *Δ* | *Rank* |
| $S_1$ | [1, 0] | 1 | 4/6 | [0.667,0] | 0.667 | 1 | [0.349,0.651] | -0.302 | 4/6 | [0.232, 0.433] | -0.201 | 2 |
| $S_2$ | [0.593,0.407] | 0.186 | 4/6 | [0.395,0.271] | 0.124 | 2 | [1, 0] | 1 | 4/6 | [0.667, 0] | 0.6667 | 1 |
| $S_3$ | [0.171,0.829] | -0.652 | 4/6 | [0.114,0.552] | -0.438 | 3 | [0.198,0.802] | -0.604 | 4/6 | [0.132,0.534] | -0.402 | 3 |
| $S_4$ | [0, 1] | -1 | 4/6 | [0, 0.667] | -0.667 | 4 | [0, 1] | -1 | 4/6 | [0, 0.667] | -0.667 | 4 |
| | *Availability ($Q_2$)* | | | | | | *Successability ($Q_4$)* | | | | | |
| | *[μ,u]* | *Δ* | *ϑ* | *Adjusted [μ,u]* | *Δ* | *Rank* | *[μ,u]* | *Δ* | *ϑ* | *Adjusted [μ,u]* | *Δ* | *Rank* |
| $S_1$ | [0,1] | -1 | 5/6 | [0, 0.833] | -0.833 | 5 | [0.113,0.887] | -0.774 | 5/6 | [0.094, 0.739] | -0.645 | 4 |
| $S_2$ | [0.943,0.057] | 0.886 | 5/6 | [0.785,0.047] | 0.738 | 2 | [1, 0] | 1 | 5/6 | [0.833, 0] | 0.833 | 1 |
| $S_3$ | [1,0] | 1 | 5/6 | [0.833,0] | 0.8333 | 1 | [0.935,0.065] | 0.871 | 5/6 | [0.779,0.054] | 0.725 | 2 |
| $S_4$ | [0.285,0.715] | -0.430 | 5/6 | [0.238,0.595] | -0.357 | 4 | [0.194,0.806] | -0.613 | 5/6 | [0.161, 0.672] | -0.511 | 3 |
| $S_5$ | [0.343,0.657] | -0.314 | 5/6 | [0.285,0.547] | -0.262 | 3 | [0, 1] | -1 | 5/6 | [0, 0.833] | -0.833 | 5 |

TABLE III: ENTROPY-OBJECTIVE WEIGHTS OF THE QUALITY ATTRIBUTES

| *Service* | *Response Time ($Q_1$)* | *Availability ($Q_2$)* | *Throughput ($Q_3$)* | *Successability ($Q_4$)* | *Weighted Correlation Coefficient ($W_i(S^*, S_i)$)* |
|---|---|---|---|---|---|
| $S_1$ | [0.667,0] | [0, 0.833] | [0.232, 0.433] | [0.094, 0.739] | 0.294 |
| $S_2$ | [0.395, 0.271] | [0.785, 0.047] | [0.667, 0] | [0.833, 0] | 0.958 |
| $S_3$ | [0.114, 0.552] | [0.833,0] | [0.132,0.534] | [0.779,0.054] | 0.733 |
| $S_4$ | [0, 0.667] | [0.238, 0.595] | [0, 0.667] | [0.161, 0.672] | 0.179 |
| $S_5$ | [0, 0] | [0.285,0.547] | [0, 0] | [0, 0.833] | 0.260 |
| **Entropy weights** | $w_1$ | $w_2$ | $w_3$ | $w_4$ | |
| | 0.206473 | 0.322511 | 0.206476 | 0.264541 | |

To rank services with regard to all attributes, we need to objectively determine attribute weights. For this purpose, we can apply a decision making method such the one proposed in (Ye, 2010) that is suitable for multi-criteria fuzzy decision making problems with unknown information on criteria weights. If information about the weight $w_j$ of attribute $Q_j$ is unknown, we calculate the entropy (objective) weight (Ye, 2010):

$$w_j = (1 - H_j) \Big/ (K - \sum_{j=1}^{K} H_j) \tag{6}$$

where $K$ is the number of attributes, $w_j \in [0,1]$, $\sum_{j=1}^{K} w_j = 1$, $N$ is the number of services, $H_j = (1/N) \sum_{i=1}^{N} (1 - \mu_j(i) - u_j(i)) = (1/N) \sum_{i=1}^{N} \pi_j(i)$, and

$1 \leq H_j \leq 1$ $(j = 1, \ldots, K)$.

The final ranking of services is derived by calculating for each service $S_i$ the weighted correlation coefficient $W_i(S^*, S_i)$ representing the distance of each service $S_i$ from the "ideal" service $S^*$, that is a service with membership equal to 1 for the level that satisfies all attributes.

$W_i(S^*, S_i)$ is calculated by using the following equation (Ye, 2010):

$$W_i(S^*, S_i) = \frac{\sum_{j=1}^{K} w_j \mu_{S_i}(Q_j)}{\sqrt{\sum_{j=1}^{K} w_j\left(\mu_{S_i}^2(Q_j) + u_{S_i}^2(Q_j)\right)}} \quad (7)$$

Table III presents the membership/non-membership values for the level at which service $S_i$ ( $i = 1..5$ ) satisfies/does not satisfy attribute $Q_j$ $(j = 1..4)$. Notice that these values are the adjusted membership/non-membership values calculated before and shown in Table II. We only take into account services $S_1..S_5$, because for these services full or partial assessments exist.

The objective entropy weight $w_j$ for each attribute $Q_j$ is computed using Eq. (6) and the results are presented in the last row of Table III. Using Eq. (7), we can get the weighted correlation coefficient for each service $S_i$, shown in last column of Table III: $W_1(S^*, S_1) = 0.294$ , $W_2(S^*, S_2) = 0.958$ , $W_3(S^*, S_3) = 0.733$ , $W_4(S^*, S_4) = 0.179$ and $W_5(S^*, S_5) = 0.260$. The larger the value of the weighted correlation coefficient, the better the alternative service is (as this service is closer to the ideal alternative). Therefore, we can conclude the final ranking of services, that is $S_2, S_3, S_1, S_5, S_4$.

# 6. ADJUSTING QUALITY ASSESSMENTS BASED ON USERS' OPINIONS

So far we only considered uncertainties related to the brokers' evaluation of services. Now we turn our attention to the users' perspective on services evaluation. In order to maintain a healthy broker service, even when all known services in a category have been assessed fully, we have to take into account users' perceptions. In the current section, we demonstrate users' uncertainty on whether the measurement presented by the broker as maximum (minimum) in a benefit (cost) attribute is satisfying. More specifically, we consider the possibility that some quality attribute values may not be satisfying for the needs of the users. Thus, even though all services in a category have been measured, the user may express some concerns regarding the minimum or the maximum measurement of a cost or benefit attribute respectively.

The approach that we follow is inspired by the method suggested in (Deng-Feng, 2011) for transforming numerical values into IFSs. Users are asked, for a full set of services in a specific category which are fully assessed, whether they believe that the measurement presented as maximum (minimum) in a benefit (cost) attribute is satisfying. This belief is a number belonging in the range [0, 1]. We consider this number to affect the membership of all the services in a category in relation to this attribute by applying a variation of Equation (3).

More specifically, considering the membership of each service $S_i$ in relation to quality attribute $k$, we have again $F_k(S_i)$, the measured value of $Q_k$ attribute for service $S_i$. Furthermore, $Q^1$ represents the benefit attributes and $Q^2$ the cost attributes. Also, $P = \max\{F_k(S_i) | i = \{1..N\}\}$ and $p = \min\{F_k(S_i) \mid i = \{1..N\}\}$ are the maximum and minimum value of alternative services in relation to attribute $Q_k$. Since all services are fully assessed, the membership of each service considering the quality attribute k is computed by Equation (8):

$$\mu_k(i) = \begin{cases} \alpha_k \times \dfrac{F_k(S_i) - p}{P - p}, \forall\, k \in Q^1 \\ \delta_k \times \dfrac{P - F_k(S_i)}{P - p}, \forall\, k \in Q^2 \end{cases} \quad (8)$$

In Equation 8, the membership ratio is multiplied by a coefficient which represents the satisfaction of the users in the respective attribute's maximum or minimum value. In the case of benefit attributes this coefficient is $\alpha_k$ whereas in the case of cost attributes is $\delta_k$.

Having the membership function, we now define the non-membership function as shown in Equation 9:

$$u_k(\mathrm{i}) = \begin{cases} (1 - \alpha_k) \times (1 - \mu_k(i)), \forall\, k \in Q^1 \\ (1 - \delta_k) \times (1 - \mu_k(i)), \forall\, k \in Q^2 \end{cases} \quad (9)$$

As can be seen from Equation 9 the non-membership of service $S_i$ in relation to quality attribute $k$, is calculated by multiplying the complement of the satisfaction coefficient, $\alpha_k$ or $\delta_k$, for benefit and cost attributes respectively, with the complement of the membership value. As per the definition of IFSs, $\pi_k(i) = 1 - \mu_k(i) - u_k(i)$, represents the hesitation degree.

The intuition behind equations 8 and 9 is the following: if the users believe that the maximum (minimum) of a benefit (cost) attribute is satisfying then the respective coefficient $\alpha_k$ ($\delta_k$) will be 1 and the membership of each service will be based solely on the distance from the trusted optimum. On the contrary, a less than 1 coefficient will signify a dissatisfaction in the optimum value and will reduce accordingly the membership part and attribute the remaining to the non-membership and hesitation parts. Notice that we do not examine the cause of the users' dissatisfaction to the reported optimum value. It may be that the users do not trust the measurement (for example 100% availability may seem too optimistic) or that the users believe that there is room for improvement and that the optimum will not be enough for their needs.

To give an example of this approach, consider the quality values reported in the QWS dataset (Al-Masri and Mahmoud, 2007a, Al-Masri and Mahmoud, 2007b). According to this dataset all the available services have been fully measured in relation to the following quality attributes (Table IV):

TABLE IV: QUALITY ATTRIBUTES OF QWS DATASET

| *Parameter Name* | *Description* | *Units* |
|---|---|---|
| Response Time | Time taken to send a request and receive a response | ms |
| Availability | Number of successful invocations/total invocations | % |
| Throughput | Total Number of invocations for a given period of time | invokes/second |
| Successability | Number of response / number of request messages | % |
| Reliability | Ratio of the number of error messages to total messages | % |
| Compliance | The extent to which a WSDL document follows WSDL specification | % |
| Best Practices | The extent to which a Web service follows WS-I Basic Profile | % |
| Latency | Time taken for the server to process a given request | ms |
| Documentation | Measure of documentation (i.e. description tags) in WSDL | % |

QWS dataset provides also an application that allows searching the dataset, using among others the type of requested service. For example, the user may search for the quality attribute measurements of the available fax services in the dataset. This dataset is depicted in Table V. In relation to these quality attributes we observe that Response Time and Latency are cost attributes and that all other attributes are benefit attributes.

Suppose now that we asked 100 users to express their satisfaction with the reported optimum value and that in all cases 90 users were satisfied with the optimum value and only 10 were not satisfied. This signifies a mostly satisfying perception of the reported measurements by the users where in all cases $\alpha_k$=0.9 and $\delta_k$=0.9.

How would this perception affect the objective ranking of the various services?

As a first step, we apply Equations 8 and 9 to calculate the membership ($\mu$), non-membership ($u$) and hesitation degree ($\pi$) of each service with respect to the various quality attributes. The results are depicted in Table VI. This table contains all the 12 fax services in the QWS dataset and for each one of the 9 quality attributes the membership, non-membership and hesitation have been calculated using equations 8 and 9. The calculations have been carried out using $\alpha_k$=0.9 and $\delta_k$=0.9. Also $F_k(S_i)$ for each attribute $k$ and service $S_i$ is given in Table V. Finally, $P$ is the maximum value and $p$ is the minimum value of each quality attribute, also mentioned in Table V.

TABLE V: QUALITY ATTRIBUTE MEASUREMENTS FOR THE FAX SERVICES IN THE QWS DATASET

| *Service* | *Response Time (ms)* | *Availability (%)* | *Throughput (hits/sec)* | *Successability (%)* | *Reliability (%)* | *Compliance (%)* | *Best Practices (%)* | *Latency (ms)* | *Documentation (%)* |
|---|---|---|---|---|---|---|---|---|---|
| ***S1*** | 71.75 | 59 | 1.2 | 60 | 67 | 100 | 77 | 4.5 | 38 |
| ***S2*** | 539.72 | 23 | 4 | 24 | 60 | 78 | 83 | 146.94 | 10 |
| ***S3*** | 79 | 83 | 32 | 84 | 78 | 89 | 89 | 3 | 67 |
| ***S4*** | 138.06 | 100 | 11 | 100 | 60 | 78 | 69 | 2.06 | 83 |
| ***S5*** | 324.44 | 31 | 4.9 | 32 | 60 | 78 | 83 | 123.94 | 11 |
| ***S6*** | 108.67 | 87 | 4.8 | 95 | 73 | 100 | 84 | 24.84 | 12 |
| ***S7*** | 332.11 | 31 | 4.5 | 31 | 60 | 78 | 83 | 118.67 | 9 |
| ***S8*** | 90 | 83 | 21.8 | 84 | 78 | 89 | 89 | 3 | 59 |
| ***S9*** | 91 | 83 | 25.8 | 84 | 78 | 89 | 89 | 3 | 64 |
| ***S10*** | 464.17 | 22 | 3.5 | 23 | 60 | 78 | 83 | 124.39 | 6 |
| ***S11*** | 148.33 | 92 | 2 | 97 | 73 | 78 | 80 | 1.66 | 93 |
| ***S12*** | 64.75 | 57 | 1.4 | 59 | 67 | 100 | 77 | 2.25 | 32 |
| Max ($P$) | 539.72 | 100 | 32 | 100 | 78 | 100 | 89 | 146.94 | 93 |
| Min ($p$) | 64.75 | 22 | 1.2 | 23 | 60 | 78 | 69 | 1.66 | 6 |

TABLE VI: MEMBERSHIP, NON-MEMBERSHIP AND HESITATION DEGREES OF FAX SERVICES IN THE QWS DATASET

| | *Response Time (ms)* | | | *Availability (%)* | | | *Throughput (hits/sec)* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *μ* | *u* | *π* | *μ* | *u* | *π* | *μ* | *u* | *π* |
| *S1* | 0.88674 | 0.01133 | 0.10194 | 0.42692 | 0.05731 | 0.51577 | 0.00000 | 0.10000 | 0.90000 |
| *S2* | 0.00000 | 0.10000 | 0.90000 | 0.01154 | 0.09885 | 0.88962 | 0.08182 | 0.09182 | 0.82636 |
| *S3* | 0.87300 | 0.01270 | 0.11430 | 0.70385 | 0.02962 | 0.26654 | 0.90000 | 0.01000 | 0.09000 |
| *S4* | 0.76109 | 0.02389 | 0.21502 | 0.90000 | 0.01000 | 0.09000 | 0.28636 | 0.07136 | 0.64227 |
| *S5* | 0.40792 | 0.05921 | 0.53287 | 0.10385 | 0.08962 | 0.80654 | 0.10812 | 0.08919 | 0.80269 |
| *S6* | 0.81678 | 0.01832 | 0.16490 | 0.75000 | 0.02500 | 0.22500 | 0.10519 | 0.08948 | 0.80532 |
| *S7* | 0.39339 | 0.06066 | 0.54595 | 0.10385 | 0.08962 | 0.80654 | 0.09643 | 0.09036 | 0.81321 |
| *S8* | 0.85215 | 0.01478 | 0.13306 | 0.70385 | 0.02962 | 0.26654 | 0.60195 | 0.03981 | 0.35825 |
| *S9* | 0.85026 | 0.01497 | 0.13477 | 0.70385 | 0.02962 | 0.26654 | 0.71883 | 0.02812 | 0.25305 |
| *S10* | 0.14316 | 0.08568 | 0.77116 | 0.00000 | 0.10000 | 0.90000 | 0.06721 | 0.09328 | 0.83951 |
| *S11* | 0.74163 | 0.02584 | 0.23253 | 0.80769 | 0.01923 | 0.17308 | 0.02338 | 0.09766 | 0.87896 |
| *S12* | 0.90000 | 0.01000 | 0.09000 | 0.40385 | 0.05962 | 0.53654 | 0.00584 | 0.09942 | 0.89474 |
| | *Successability (%)* | | | *Reliability (%)* | | | *Compliance (%)* | | |
| | *μ* | *u* | *π* | *μ* | *u* | *π* | *μ* | *u* | *π* |
| *S1* | 0.43247 | 0.05675 | 0.51078 | 0.35000 | 0.06500 | 0.58500 | 0.90000 | 0.01000 | 0.09000 |
| *S2* | 0.01169 | 0.09883 | 0.88948 | 0.00000 | 0.10000 | 0.90000 | 0.00000 | 0.10000 | 0.90000 |
| *S3* | 0.71299 | 0.02870 | 0.25831 | 0.90000 | 0.01000 | 0.09000 | 0.45000 | 0.05500 | 0.49500 |
| *S4* | 0.90000 | 0.01000 | 0.09000 | 0.00000 | 0.10000 | 0.90000 | 0.00000 | 0.10000 | 0.90000 |
| *S5* | 0.10519 | 0.08948 | 0.80532 | 0.00000 | 0.10000 | 0.90000 | 0.00000 | 0.10000 | 0.90000 |
| *S6* | 0.84156 | 0.01584 | 0.14260 | 0.65000 | 0.03500 | 0.31500 | 0.90000 | 0.01000 | 0.09000 |
| *S7* | 0.09351 | 0.09065 | 0.81584 | 0.00000 | 0.10000 | 0.90000 | 0.00000 | 0.10000 | 0.90000 |
| *S8* | 0.71299 | 0.02870 | 0.25831 | 0.90000 | 0.01000 | 0.09000 | 0.45000 | 0.05500 | 0.49500 |
| *S9* | 0.71299 | 0.02870 | 0.25831 | 0.90000 | 0.01000 | 0.09000 | 0.45000 | 0.05500 | 0.49500 |
| *S10* | 0.00000 | 0.10000 | 0.90000 | 0.00000 | 0.10000 | 0.90000 | 0.00000 | 0.10000 | 0.90000 |
| *S11* | 0.86494 | 0.01351 | 0.12156 | 0.65000 | 0.03500 | 0.31500 | 0.00000 | 0.10000 | 0.90000 |
| *S12* | 0.42078 | 0.05792 | 0.52130 | 0.35000 | 0.06500 | 0.58500 | 0.90000 | 0.01000 | 0.09000 |
| | *Best Practices (%)* | | | *Latency (ms)* | | | *Documentation (%)* | | |
| | *μ* | *u* | *π* | *μ* | *u* | *π* | *μ* | *u* | *π* |
| *S1* | 0.36000 | 0.06400 | 0.57600 | 0.88241 | 0.01176 | 0.10583 | 0.33103 | 0.06690 | 0.60207 |
| *S2* | 0.63000 | 0.03700 | 0.33300 | 0.00000 | 0.10000 | 0.90000 | 0.04138 | 0.09586 | 0.86276 |
| *S3* | 0.90000 | 0.01000 | 0.09000 | 0.89170 | 0.01083 | 0.09747 | 0.63103 | 0.03690 | 0.33207 |
| *S4* | 0.00000 | 0.10000 | 0.90000 | 0.89752 | 0.01025 | 0.09223 | 0.79655 | 0.02034 | 0.18310 |
| *S5* | 0.63000 | 0.03700 | 0.33300 | 0.14248 | 0.08575 | 0.77176 | 0.05172 | 0.09483 | 0.85345 |
| *S6* | 0.67500 | 0.03250 | 0.29250 | 0.75640 | 0.02436 | 0.21924 | 0.06207 | 0.09379 | 0.84414 |
| *S7* | 0.63000 | 0.03700 | 0.33300 | 0.17513 | 0.08249 | 0.74238 | 0.03103 | 0.09690 | 0.87207 |
| *S8* | 0.90000 | 0.01000 | 0.09000 | 0.89170 | 0.01083 | 0.09747 | 0.54828 | 0.04517 | 0.40655 |
| *S9* | 0.90000 | 0.01000 | 0.09000 | 0.89170 | 0.01083 | 0.09747 | 0.60000 | 0.04000 | 0.36000 |
| *S10* | 0.63000 | 0.03700 | 0.33300 | 0.13970 | 0.08603 | 0.77427 | 0.00000 | 0.10000 | 0.90000 |
| *S11* | 0.49500 | 0.05050 | 0.45450 | 0.90000 | 0.01000 | 0.09000 | 0.90000 | 0.01000 | 0.09000 |
| *S12* | 0.36000 | 0.06400 | 0.57600 | 0.89634 | 0.01037 | 0.09329 | 0.26897 | 0.07310 | 0.65793 |

Then we apply the same procedure as in Section 5 to produce the objective ranking of the various services which now includes also the users' perceptions regarding reported optimum values.

The entropy (objective) weight for each quality attribute can be computed by using Eq. 6. The results are depicted in Table VII. Then we calculate the nominator and denominator of Equation 7 and compute the weighted correlation coefficient. The results are depicted in Table VIII.

TABLE VII: ENTROPY WEIGHTS FOR THE QUALITY ATTRIBUTES OF THE FAX SERVICES IN THE QWS DATASET

| | | | |
|---|---|---|---|
| ***Response Time (ms)*** | 0.14536 | ***Availability (%)*** | 0.11280 |
| ***Throughput (hits/sec)*** | 0.07023 | ***Successability (%)*** | 0.11588 |
| ***Reliability (%)*** | 0.09789 | ***Compliance (%)*** | 0.08734 |
| ***Best Practices (%)*** | 0.13699 | ***Latency (ms)*** | 0.14275 |
| ***Documentation (%)*** | 0.09078 | | |

TABLE VIII: RANKING BASED ON WEIGHTED CORRELATION COEFFICIENT

| ***Service*** | (a) $\sum_{j=1}^{K} w_j \mu_{S_i}(Q_j)$ | (b) $\sqrt{\sum_{j=1}^{K} w_j \begin{pmatrix} \mu_{S_i}^2(Q_j) \\ +v_{S_i}^2(Q_j) \end{pmatrix}}$ | (a)/(b) $W_i(S^*, S_i)$ |
|---|---|---|---|
| ***S3*** | 0.78737 | 0.80043 | 0.98369 |
| ***S9*** | 0.76853 | 0.78167 | 0.98319 |
| ***S8*** | 0.75590 | 0.77158 | 0.97968 |
| ***S6*** | 0.65654 | 0.70829 | 0.92693 |
| ***S11*** | 0.64239 | 0.71172 | 0.90259 |
| ***S1*** | 0.54536 | 0.61724 | 0.88354 |
| ***S12*** | 0.54009 | 0.61756 | 0.87456 |
| ***S4*** | 0.53698 | 0.67195 | 0.79914 |
| ***S5*** | 0.20213 | 0.30303 | 0.66703 |
| ***S7*** | 0.20062 | 0.30173 | 0.66490 |
| ***S10*** | 0.13177 | 0.26157 | 0.50376 |
| ***S2*** | 0.09846 | 0.25220 | 0.39039 |

Services in Table VIII are ranked according to the value of the weighted correlation coefficient. The first service is the 3rd service (S3) and the worst service is the 2nd service (S2). The intuition behind this ranking is that services which present higher membership values in quality attributes with greater variability are ranked higher.

## 7. USER SPECIFIC RANKING OF SERVICES WITH THE TOPSIS METHOD

The previous sections have handled the uncertainty caused by suitable known services that may have not been assessed completely as well as the uncertainty caused by the minimum or maximum values of cost and benefit attributes, respectively. In this section, we discuss our approach in generating a user-specific (i.e. subjective) ranking based on vague users' preferences on the importance of QoS attributes. In particular, QoS attributes are strongly affected by users' perceptions and their preferences can be expressed as linguistic terms which are then mapped to IFSs. To achieve this, we apply a TOPSIS-based technique for IFSs, like the one introduced in (Boran et al., 2009).

First, a weighted intuitionistic fuzzy quality matrix (*WIFQM*) is composed by considering the intuitionistic fuzzy quality matrix (*IFQM*) (e.g. Table VI produced in the previous section for the fax service data set) and a vector of the attribute weights *W* provided by a user, in which the user expresses the importance of each quality attribute for his/her specific needs. This step is necessary to synthesize the ratings of brokers with the needs of the users.

To compose the *WIFQM*, we will need to utilize the matrix multiplication operator, as it is defined for IFSs as follows (Atanassov, 1986):

$$IFQM \otimes W = \{< x, \mu_{A_i}(x) \cdot \mu_W(x), \\ u_{A_i}(x) + u_W(x) - u_{A_i}(x) \cdot u_W(x) > | x \in X\} \quad (10)$$

According to this operator the intuitionistic fuzzy quality matrix (*IFQM* in Equation 10) is multiplied by the vector of attribute weights *W* provided by the user which is also a vector of intuitionistic fuzzy numbers. Users provide their weights using linguistic terms signifying the importance of each quality attribute for their specific purpose. These linguistic terms are mapped to Intuitionistic Fuzzy Numbers (IFNs) using Table IX. It should be noted that linguistic terms shown in Table IX can be related with variable hesitation degrees. In Table IX as an example we provide indicative hesitation values which are 0.00 for strong assessments and 0.05 otherwise. However, users can select different hesitation degrees following the approach presented in (Wang 2009).

TABLE IX: MAPPING OF LINGUISTIC TERMS TO IFNS

| ***Linguistic Terms*** | $\mu_\kappa$ | $u_\kappa$ | $\pi_\kappa$ |
|---|---|---|---|
| Very Important (VI) | 0.90 | 0.10 | 0.00 |

| | | | |
|---|---|---|---|
| Important (I) | 0.75 | 0.20 | 0.05 |
| Of Medium Importance (M) | 0.50 | 0.45 | 0.05 |
| Unimportant (U) | 0.35 | 0.60 | 0.05 |
| Very Unimportant (VU) | 0.10 | 0.90 | 0.00 |

Suppose for example that the user has provided the linguistic terms shown in Table X for the quality attributes of a fax service that she/he requires.

TABLE X: USER PREFERENCES FOR THE FAX SERVICE EXAMPLE

| ***Response Time*** | ***Availability*** | ***Throughput*** |
|---|---|---|
| VI [0.90, 0.10, 0] | I [0.75, 0.20, 0.05] | VI [0.90, 0.10, 0] |
| ***Successability*** | ***Reliability*** | ***Compliance*** |
| M [0.50, 0.45, 0.05] | VI [0.90, 0.10, 0] | U [0.35, 0.60, 0.05] |
| ***Best Practices*** | ***Latency*** | ***Documentation*** |
| U [0.35, 0.60, 0.05] | VI [0.90, 0.10, 0] | U [0.35, 0.60, 0.05] |

Then, we compute the intuitionistic fuzzy positive ideal solution ($A^*$) and the intuitionistic fuzzy negative ideal solution ($A^-$) in order to apply the TOPSIS method. Both solutions are vectors of IFN elements and they are derived from the *WIFQM* matrix as follows. Let $B$ and $C$ be the sets of benefit and cost quality attributes, respectively. $A^*$ and $A^-$ are equal to:

$$
\begin{aligned}
&\mathrm{A}^* = \left(\mu_{A^*W}(x_j), u_{A^*W}(x_j)\right) \\
&A^- = \left(\mu_{A^-W}(x_j), u_{A^-W}(x_j)\right), \text{ where:} \\
&\mu_{A^*W}(x_j) = ((\max_i \mu_{A_iW}(x_j)|j \in B), \\
&\qquad (\min_i \mu_{A_iW}(x_j)|j \in C)) \\
&u_{A^*W}(x_j) = ((\min_i u_{A_iW}(x_j)|j \in B), \\
&\qquad (\max_i u_{A_iW}(x_j)|j \in C)) \\
&\mu_{A^-W}(x_j) = ((\min_i \mu_{A_iW}(x_j)|j \in B), \\
&\qquad (\max_i \mu_{A_iW}(x_j)|j \in C)) \\
&u_{A^-W}(x_j) = ((\max_i u_{A_iW}(x_j)|j \in B), \\
&\qquad (\max_i u_{A_iW}(x_j)|j \in C))
\end{aligned}
\tag{11}
$$

For the Fax Service QWS data set $B$={Availability, Successability, Compliance, Throughput, Reliability, Best Practices, Documentation} and $C$={Response time, Latency}. To obtain $A^*$ and $A^-$, Eq. (11) is applied on the IFNs of the *WIFQM* decision matrix. The $A$* (positive ideal solution) and $A$- (negative ideal solution) are determined as follows:

$A^*$= (Response Time, Availability, Throughput, Successability, Reliability, Compliance, Best Practices, Latency, Documentation) =

([0, 0.19, 0.81], [0.675, 0.208, 0.117], [0.81, 0.109, 0.081], [0.45, 0.4555, 0.0945], [0.81, 0.109, 0.081], [0.315, 0.604,0.081], [0.315, 0.604, 0.081], [0, 0.19, 0.81], [0.315, 0.604, 0.081])

$A^-$ = (Response Time, Availability, Throughput, Successability, Reliability, Compliance, Best Practices, Latency, Documentation) =

([0.81, 0.109, 0.081], [0, 0.28, 0.72], [0, 0.19, 0.81], [0, 0.505, 0.495], [0, 0.19, 0.81], [0, 0.64, 0.36], [0, 0.64, 0.36], [0.81, 0.109, 0.081], [0, 0.64, 0.36])

Next, separation (distance) measures can be calculated for each candidate service $S_i$ from $A^*$ and the $A^-$, respectively. The normalized Euclidean distance can be adopted, since it has been proven to be a reliable distance measure that takes into account not only membership and non-membership but also the hesitation part of IFNs (Szmidt and Kacprzyk, 2000). For each alternative service two separation values can be calculated by applying Equations (12) and (13). By utilizing these equations, the positive and negative separation measures can be computed for the twelve alternative services. These values are shown in columns (1) and (2) of Table XII.

$$
M^* = \sqrt{\frac{1}{2N}\sum_{j=1}^{N}\begin{bmatrix}\left(\mu_{A_iW}(x_j) - \mu_{A^*W}(x_j)\right)^2 + \\ \left(u_{A_iW}(x_j) - u_{A^*W}(x_j)\right)^2 + \\ \left(\pi_{A_iW}(x_j) - \pi_{A^*W}(x_j)\right)^2\end{bmatrix}}
\tag{12}
$$

TABLE XII: SEPARATION MEASURES OF THE CANDIDATE SERVICES

| | ***$M^*$ (1)*** | ***$M^-$ (2)*** | ***$C_{i^*}$ (3)*** |
|---|---|---|---|
| ***S1*** | 0.495 | 0.189 | 0.277 |
| ***S2*** | 0.453 | 0.362 | 0.444 |
| ***S3*** | 0.366 | 0.425 | 0.537 |
| ***S4*** | 0.480 | 0.279 | 0.368 |
| ***S5*** | 0.452 | 0.264 | 0.369 |
| ***S6*** | 0.411 | 0.312 | 0.432 |
| ***S7*** | 0.455 | 0.258 | 0.363 |
| ***S8*** | 0.373 | 0.381 | 0.505 |
| ***S9*** | 0.366 | 0.397 | 0.521 |
| ***S10*** | 0.462 | 0.307 | 0.399 |
| ***S11*** | 0.438 | 0.316 | 0.419 |
| ***S12*** | 0.501 | 0.185 | 0.270 |

The final score of each service can be derived by calculating the corresponding relative closeness coefficient with respect to the intuitionistic fuzzy ideal solution. For each alternative service $S_i$, the relative closeness coefficient with respect to $A^+$ is defined by Equation (14).

$$
C_{i^*} = \frac{M_{i^-}}{M_{i^*} + M_{i^-}}, 0 \leq C_{i^*} \leq 1
\tag{14}
$$

TABLE XI: WEIGHTED INTUITIONISTIC FUZZY QUALITY MATRIX

| | *Response Time (ms)* | | | *Availability (%)* | | | *Throughput (hits/sec)* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *μ* | *υ* | *π* | *μ* | *υ* | *π* | *μ* | *υ* | *π* |
| ***S1*** | 0.79806 | 0.11019 | 0.09174 | 0.32019 | 0.24585 | 0.43396 | 0.00000 | 0.19000 | 0.81000 |
| ***S2*** | 0.00000 | 0.19000 | 0.81000 | 0.00865 | 0.27908 | 0.71227 | 0.07364 | 0.18264 | 0.74373 |
| ***S3*** | 0.78570 | 0.11143 | 0.10287 | 0.52788 | 0.22369 | 0.24842 | 0.81000 | 0.10900 | 0.08100 |
| ***S4*** | 0.68498 | 0.12150 | 0.19352 | 0.67500 | 0.20800 | 0.11700 | 0.25773 | 0.16423 | 0.57805 |
| ***S5*** | 0.36713 | 0.15329 | 0.47958 | 0.07788 | 0.27169 | 0.65042 | 0.09731 | 0.18027 | 0.72243 |
| ***S6*** | 0.73510 | 0.11649 | 0.14841 | 0.56250 | 0.22000 | 0.21750 | 0.09468 | 0.18053 | 0.72479 |
| ***S7*** | 0.35405 | 0.15459 | 0.49135 | 0.07788 | 0.27169 | 0.65042 | 0.08679 | 0.18132 | 0.73189 |
| ***S8*** | 0.76694 | 0.11331 | 0.11975 | 0.52788 | 0.22369 | 0.24842 | 0.54175 | 0.13582 | 0.32242 |
| ***S9*** | 0.76523 | 0.11348 | 0.12129 | 0.52788 | 0.22369 | 0.24842 | 0.64695 | 0.12531 | 0.22775 |
| ***S10*** | 0.12884 | 0.17712 | 0.69404 | 0.00000 | 0.28000 | 0.72000 | 0.06049 | 0.18395 | 0.75556 |
| ***S11*** | 0.66747 | 0.12325 | 0.20928 | 0.60577 | 0.21538 | 0.17885 | 0.02104 | 0.18790 | 0.79106 |
| ***S12*** | 0.81000 | 0.10900 | 0.08100 | 0.30288 | 0.24769 | 0.44942 | 0.00526 | 0.18947 | 0.80527 |
| | *Successability (%)* | | | *Reliability (%)* | | | *Compliance (%)* | | |
| | *μ* | *υ* | *π* | *μ* | *υ* | *π* | *μ* | *υ* | *π* |
| ***S1*** | 0.21623 | 0.48121 | 0.30255 | 0.31500 | 0.15850 | 0.52650 | 0.31500 | 0.60400 | 0.08100 |
| ***S2*** | 0.00584 | 0.50436 | 0.48980 | 0.00000 | 0.19000 | 0.81000 | 0.00000 | 0.64000 | 0.36000 |
| ***S3*** | 0.35649 | 0.46579 | 0.17772 | 0.81000 | 0.10900 | 0.08100 | 0.15750 | 0.62200 | 0.22050 |
| ***S4*** | 0.45000 | 0.45550 | 0.09450 | 0.00000 | 0.19000 | 0.81000 | 0.00000 | 0.64000 | 0.36000 |
| ***S5*** | 0.05260 | 0.49921 | 0.44819 | 0.00000 | 0.19000 | 0.81000 | 0.00000 | 0.64000 | 0.36000 |
| ***S6*** | 0.42078 | 0.45871 | 0.12051 | 0.58500 | 0.13150 | 0.28350 | 0.31500 | 0.60400 | 0.08100 |
| ***S7*** | 0.04675 | 0.49986 | 0.45339 | 0.00000 | 0.19000 | 0.81000 | 0.00000 | 0.64000 | 0.36000 |
| ***S8*** | 0.35649 | 0.46579 | 0.17772 | 0.81000 | 0.10900 | 0.08100 | 0.15750 | 0.62200 | 0.22050 |
| ***S9*** | 0.35649 | 0.46579 | 0.17772 | 0.81000 | 0.10900 | 0.08100 | 0.15750 | 0.62200 | 0.22050 |
| ***S10*** | 0.00000 | 0.50500 | 0.49500 | 0.00000 | 0.19000 | 0.81000 | 0.00000 | 0.64000 | 0.36000 |
| ***S11*** | 0.43247 | 0.45743 | 0.11010 | 0.58500 | 0.13150 | 0.28350 | 0.00000 | 0.64000 | 0.36000 |
| ***S12*** | 0.21039 | 0.48186 | 0.30775 | 0.31500 | 0.15850 | 0.52650 | 0.31500 | 0.60400 | 0.08100 |
| | *Best Practices (%)* | | | *Latency (ms)* | | | *Documentation (%)* | | |
| | *μ* | *υ* | *π* | *μ* | *υ* | *π* | *μ* | *υ* | *π* |
| ***S1*** | 0.12600 | 0.62560 | 0.24840 | 0.79417 | 0.11058 | 0.09525 | 0.11586 | 0.62676 | 0.25738 |
| ***S2*** | 0.22050 | 0.61480 | 0.16470 | 0.00000 | 0.19000 | 0.81000 | 0.01448 | 0.63834 | 0.34717 |
| ***S3*** | 0.31500 | 0.60400 | 0.08100 | 0.80253 | 0.10975 | 0.08772 | 0.22086 | 0.61476 | 0.16438 |
| ***S4*** | 0.00000 | 0.64000 | 0.36000 | 0.80777 | 0.10922 | 0.08301 | 0.27879 | 0.60814 | 0.11307 |
| ***S5*** | 0.22050 | 0.61480 | 0.16470 | 0.12824 | 0.17718 | 0.69459 | 0.01810 | 0.63793 | 0.34397 |
| ***S6*** | 0.23625 | 0.61300 | 0.15075 | 0.68076 | 0.12192 | 0.19731 | 0.02172 | 0.63752 | 0.34076 |
| ***S7*** | 0.22050 | 0.61480 | 0.16470 | 0.15762 | 0.17424 | 0.66814 | 0.01086 | 0.63876 | 0.35038 |
| ***S8*** | 0.31500 | 0.60400 | 0.08100 | 0.80253 | 0.10975 | 0.08772 | 0.19190 | 0.61807 | 0.19003 |
| ***S9*** | 0.31500 | 0.60400 | 0.08100 | 0.80253 | 0.10975 | 0.08772 | 0.21000 | 0.61600 | 0.17400 |
| ***S10*** | 0.22050 | 0.61480 | 0.16470 | 0.12573 | 0.17743 | 0.69685 | 0.00000 | 0.64000 | 0.36000 |
| ***S11*** | 0.17325 | 0.62020 | 0.20655 | 0.81000 | 0.10900 | 0.08100 | 0.31500 | 0.60400 | 0.08100 |
| ***S12*** | 0.12600 | 0.62560 | 0.24840 | 0.80671 | 0.10933 | 0.08396 | 0.09414 | 0.62924 | 0.27662 |

Equation (14) can be used to calculate these coefficients (i.e., the final scores of services) listed in column (3) of Table XII. The alternative services are ranked in a descending order of these scores as can be seen in Table XIII.

Services *S3*, *S9* and *S8* ranked with high scores by the objective ranking (Table VIII) are also the dominant services in the subjective ranking (Table XIII). Regarding some of the differences from the results of the objective ranking, we can observe the following:

1. Service *S2* in the objective ranking of Table VIII was ranked as the worst service. This service in the subjective ranking for the hypothetical user of our example is ranked much higher in the 4th place (Table XIII). This is explained since some of the worst IFNs of *S2* belong to quality attributes that the user characterized as unimportant (e.g. Compliance(*S2*) = [0, 0.1, 0.9] and Documentation(*S2*) = [0.04138, 0.09586, 0.86276]).
2. Similarly, service S10 ranked 11th in the objective ranking of Table VIII. In the subjective ranking of Table XIII it is ranked 7th. Service S10 also has some of the worst values in unimportant quality attributes of the user (e.g.Compliance(S10)=[0, 0.1, 0.9], Documentation(S10) = [0, 0.1, 0.9]).
3. On the contrary, service S1 ranked 6th in the objective ranking of Table VIII and 11th in the subjective ranking of Table XIII. The much lower rank of Service S1 in the subjective ranking can be explained by the relatively low IFNs that displays in very important quality attributes for the hypothetical user (e.g. Throughput(S1) = [0, 0.1, 0.9], Reliability(S1)=[0.35, 0.065, 0.585]).

TABLE XIII: FINAL RANKING OF ALTERNATIVE SERVICES

| ***Service Name*** | $C_{i^*}$ |
|---|---|
| ***S3*** | 0.537 |
| ***S9*** | 0.521 |
| ***S8*** | 0.505 |
| ***S2*** | 0.444 |
| ***S6*** | 0.432 |
| ***S11*** | 0.419 |
| ***S10*** | 0.399 |
| ***S5*** | 0.369 |
| ***S4*** | 0.368 |
| ***S7*** | 0.363 |
| ***S1*** | 0.277 |
| ***S12*** | 0.270 |

# 8. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Most of web service ranking techniques assume a closed set of fully assessed candidates. We presented an objective ranking approach based on Intuitionistic Fuzzy Sets that considers hesitation in service quality assessment when the candidate service set has not been fully assessed yet with respect to all service quality attributes and, thus, some quality attribute values are not yet available. Furthermore, other sources of uncertainty were also handled. Uncertainty of users to accept the optimum values provided by the broker for each service category can lead to changes in the evaluations for the membership, non-membership and hesitation for all the services in a category. Similarly, users are uncertain, most often, for the exact values or values' ranges that the QoS attributes should have to satisfy their needs. Again in this case the uncertainty was handled using IFSs. More specifically, users provide linguistic terms characterizing the relative importance of each attribute, and these terms are mapped to IFNs which are used as weights for the subjective ranking of the categories' services for each user. We applied our approach to a real dataset of web services, namely the QWS dataset (Al-Masri and Mahmoud, 2007b, Al-Masri and Mahmoud, 2007c) from which we used a set of twelve services for the fax domain (category) with nine different quality attributes. Currently, we are working in developing a working software prototype for a repository of services that will be based on the described approach in this work.

In Section 6 concerning adjustment of quality assessments based on users' opinions in Eq. 8 $\alpha_k$ and $\delta_k$ represent the perception of users about the suitability of maximum and minimum values measured for a service in a specific quality attribute. However, this in turn can be affected by the evaluation of all services in a category since the minimum and maximum values may change if another service appears and we measure it. This is why in this scenario we assume that all services have been evaluated fully. Assume now that although users have expressed their perceptions about minimum and maximum values an unassessed service appears. Then the horizon factor $\vartheta$ will "kick in" and membership, non-membership and hesitation should be modified. Thus $\mu$ and $u$ will be readjusted to compensate for the lack of knowledge concerning the unassessed service. Should we remove the effect of $\alpha_k$ and $\delta_k$ prior to applying the horizon factor $\vartheta$ in this case? We think we should because $\alpha_k$ and $\delta_k$ are affected by the current minimum and maximum values at the time of users' assessment and these values may change when we measure the new service. However, this sequence of events needs to be investigated more carefully in the future. In order to do this, we will need to conduct controlled experiments with real users of web services.


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