

Reaching consensus: A moderated fuzzy web services discovery method

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Abstract

Web services are used for developing and integrating highly distributed and heterogeneous systems in different domains such as e-business, grid services, and e-government systems. Web services discovery is a key to dynamically locating desired web services across the Internet. Prevailing research trend is to dynamically discover and compose web services in order to develop composite services that provide enhanced functionality. Existing discovery techniques do not take into account the diverse preferences and expectations of service consumers and providers which are generally used for searching or advertising web services. This paper presents a moderated fuzzy web service discovery approach to model subjective and fuzzy opinions, and to assist service consumers and providers in reaching a consensus. The method achieves a common consensus on the distinct opinions and expectations of service consumers and providers. This process is iterative such that further fuzzy opinions and preferences can be added to improve the precision of web service discovery. The proposed method is implemented as a prototype system and is tested through various experiments. Experimental results demonstrate the effectiveness of the proposed method.

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1. Introduction

The flexibility, the standardized interfaces, and communication protocols of web services provide organizations with unprecedented opportunities to rethink the way in which they cooperate with each other. However, the potential of web services cannot be fully appreciated, unless meaningful and useful composition of existing web services can take place to create value-added services. The success of web service composition relies on an effective discovery mechanism which can precisely discover required web services. In order to discover required web services, discovery mechanisms incorporate functional (i.e. functionality of a web service) and non-functional (i.e. quality of service) aspects of web services. For instance, a travel agent may need to find a cheaper and convenient flight to a particular destination using various airline web services. Such airline web services may provide similar functions, but with varying degrees of quality of

services. In the context of this work, the quality of service means the contents of web services. Current practice, in service discovery mechanisms, for locating the required service (e.g. cheaper and convenient flight) is to exhaustively interrogate data repositories of individual airline web services which maintain detailed information such as a list of flights, their prices, timetables, etc. This approach incurs processing overhead as the contents of each data repository need to be searched in order to locate the required service.

Our previous work [1] presents a moderated fuzzy method in order to effectively discover required web services. The premise is to summarize the contents of data repositories and represent them at higher levels of abstraction using fuzzy terms. This enables the discovery mechanism to locate required services by looking up the summarized contents of data repositories. However, the precision of the discovery of the required services lies in an appropriate representation in fuzzy terms. Specifically, such terms should be consistently defined by the service providers and service consumers. However, the consistent definition of fuzzy terms by service providers and consumers is problematic, as they have diverse expectations and experiences on different services. This issue is further complicated by the divergence among their preferences over the selection criteria. This work attempts to alleviate these problems by proposing a consensus-based web service

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discovery architecture that enables service consumers and providers to reach a consensus on their expectations and preference criteria over service-related fuzzy terms. The potential contribution of this work is that the service consumers and providers can be aware of each other’s expectation and preference. So, they can moderate their requests and advertisements by adopting reasonable terms which conform to their consensus. The definition of the terms can be adjusted flexibly to meet the dynamic environment. The resulting system will increase the success rate for a web service consumer in discovering the required services. The service providers are able to moderate the representation of the services. Consequently, service discovery is significantly improved.

The paper is structured as follows. Section 2 provides an overview of the proposed architecture. The moderation process is introduced in Section 3. Section 4 illustrates the moderated fuzzy discovery method through an example case study. Section 5 reports on the results produced by different methods. Section 6 discusses the main features of this work and also reviews related work. Section 7 concludes the paper.

2. A moderated fuzzy web service discovery architecture

The aim of this research is to provide an architecture that allows the service providers and consumers to be aware of their expectations and preferences in order to moderate their requests and advertisements. The architecture of the proposed Moderated Fuzzy Discovery Method (MFDM) is shown in Fig. 1. It provides an environment for service providers and consumers to represent their services and requests in a way that can automatically be interpreted by software applications. It enables service providers to advertise their services with a lesser subjectivity by considering service consumers’ expectations and preferences. Consequently, service consumers have a greater chance of precisely locating their required services.

The proposed architecture comprises of different components, including fuzzy classifier, fuzzy engine, UDDI, OWL-S, a fuzzy discovery and a fuzzy moderator.

A *fuzzy classifier* contains essential predefined knowledge for interpreting and classifying the information residing in web services. It consists of primitive and composite fuzzy terms, modifier and quantification fuzzy terms, and fuzzy rules (i.e. inference rules for the fuzzy classifier). Primitive terms are a set of atomic terms that represent a collection of raw data. Composite terms are generated through the combination of primitive terms and fuzzy rules. Composite terms can also be represented in fuzzy rules, whenever heuristic associations between terms are required. The quantification terms are used to model the probabilities of occurrences. Thus the statement can be altered by a modifier, thereby making the statement a little more imprecise. In other words, the statements associated with quantification and modifier terms are represented in fuzzy rules for the purpose of reasoning. The fuzzy classifier extends the aforementioned rules and their combinations to provide powerful classifications on the data residing in services in order to produce informative declarations. A *fuzzy engine* is used to drive the fuzzy classifier to carry out classification and evaluate the values of quality of service (QoS) for web services.

The terms, which are represented with KIF (Knowledge Interchange Format) in Effect of Process class of the OWL-S [2], are declarative facts supported by other fuzzy terms and rules. The supporting fuzzy rules and sets are considered as ontologies represented in OWL for further reasoning.

The proposed MFDM adopts a standard UDDI as a tool for advertising web services. However, the information represented in UDDI lacks well-defined meaning. Thus it cannot fully support the automation of service discovery. With the complimentary support from semantic web technology, the information in UDDI can be modeled in OWL-S and OWL. Retaining a list of semantic web services in UDDI provides a convenient way to discover web services, as the grounding profile in OWL-S is able to locate

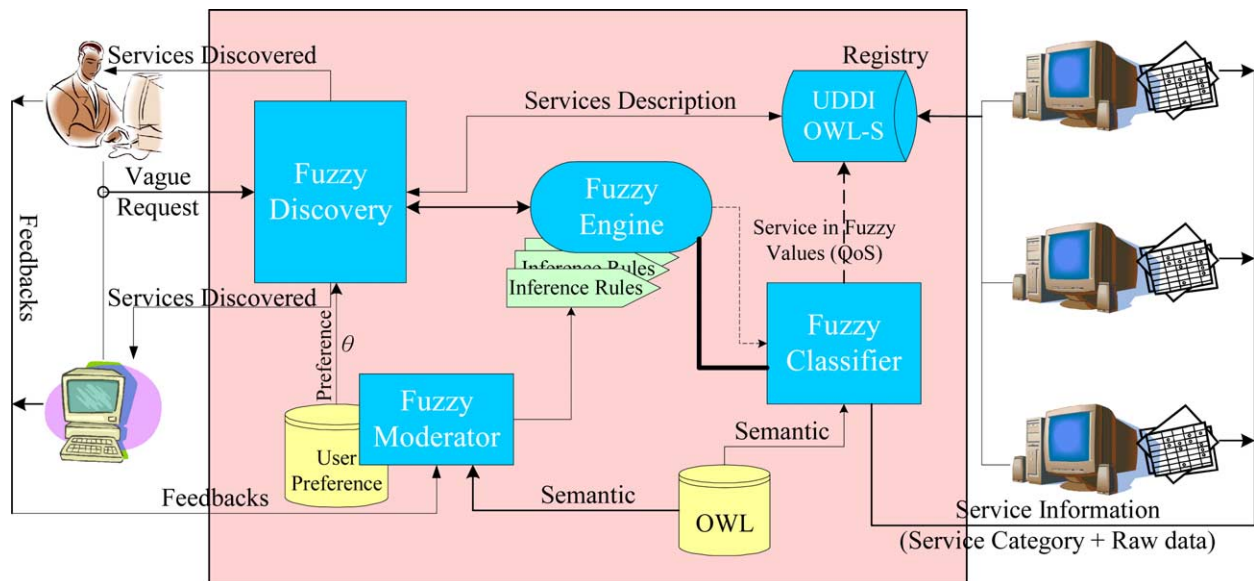


Fig. 1. The proposed architecture for moderated fuzzy discovery method (MFDM).

WSDL documents and the associated web services. The description of services can be machine-understandable notations. The mappings between UDDI and OWL-S developed by Paolucci et al. [3] enable them to work seamlessly together for the web service discovery.

The proposed architecture includes a function that can convert crisp requests from service consumers into fuzzy requests. It is important to have crisp terms transformed into fuzzy terms for the use of approximate reasoning, as contents of services have been represented in fuzzy terms. The detailed descriptions on the fuzzy discovery method can be found in our previous work [1,4].

The *fuzzy moderator* implements a moderation method (a key feature of the proposed approach) that bridges the gap between the expectations and preferences of service providers and service consumers. This mechanism assists the service consumers and providers in reaching consensus on using the fuzzy terms and the preferences over the selection criteria. It is assumed that the web services consumers and providers possess different opinions and preferences on the required services. The moderation mechanism ensures consensus by taking into account those opinions and preferences which are accepted by the majority of service providers and consumers.

The fuzzy moderator is able to incorporate iteratively users' subjective opinions and preferences and transform them to less subjective ones. In principle, the more feedbacks from users, the less subjective. This is due to the generalization of their opinions and expectations.

Therefore, the inference rules (fuzzy rules) can be moderated with less subjective opinions. Consequently, consumers are expected to have greater level of satisfaction with the services, as the gaps between the consumers' and providers' expectations can be reduced after the moderation process has been carried out. A more detailed explanation about the moderation method is provided in Section 3.

A number of tools are used for the implementation of the proposed system. The web services are implemented via JAXRPC [5] and their associated database systems are designed in MS Access. The ontologies are defined through Protégé OWLJESSKB [6], which is able to interpret OWL syntax, and is employed for the reasoning processes. Extra functionalities are added to OWLJESSKB in order to reason over fuzzy rules and sets.

3. Moderation method

The fuzzy moderated Discovery Method or MFDM comprises two parts: Similarity Aggregation Method (SAM) [7,8], and Resolution Method for Group Decision Problems (RMGDP) [9–13]. SAM and RMGDP are processed in a sequence such that SAM is initiated first to gain the consensus on distinct opinions and preferences. RMGDP then obtains the group preferences on the selection criteria.

3.1. Similarity aggregation method—SAM

The adoption of SAM is to resolve different opinions about the terms used by service providers and consumers. SAM aggregates

different users' fuzzy opinions to reach a group's fuzzy consensus opinion. It employs a similarity measure to calculate the differences between one individual with the others within the group in order to obtain the index of consensus. The index of consensus for each individual can be collected as a set in order to form an agreement among a group. SAM ensures the consistency of the definitions of fuzzy terms. It involves the following steps.

Step 1. Each user represents his/her subjective fuzzy preference on one specific criterion with a positive trapezoidal fuzzy number. A trapezoidal fuzzy number can be denoted as $\tilde{Q}_i(a_i, b_i, c_i, d_i)$, where $a_i \leq b_i \leq c_i \leq d_i$. $u_{\tilde{Q}_i}(x)$ is the membership function for \tilde{Q}_i and the value of user's subjective preference occurs between $[a_i, d_i]$. If the value of x falls between $[b_i, c_i]$, $USER_i$ subjectively considers the criterion as 1; that is $u_{\tilde{Q}_i}(x) = 1$. This is shown in Fig. 2.

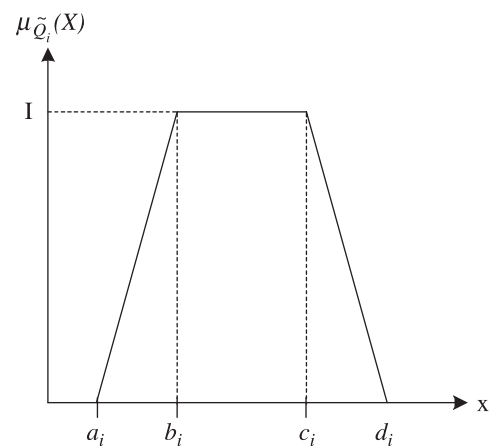


Fig. 2. A trapezoidal fuzzy number.

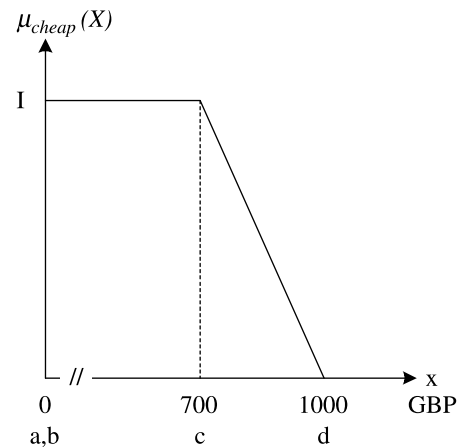


Fig. 3. $\tilde{C}_{init} = (0, 0, 700, 1000)$.

Step 2. This step obtains opinion similarity between $USER_i$ and $USER_j$. That is, $\tilde{Q}_i(a_i, b_i, c_i, d_i)$ and $\tilde{Q}_j(a_j, b_j, c_j, d_j)$ can be calculated by the similarity measure function denoted as $S_{ij} = S(\tilde{Q}_i, \tilde{Q}_j)$

$$S(\tilde{Q}_i, \tilde{Q}_j) = \frac{\int_x (\min\{u_{cheap_i}(x), u_{cheap_j}(x)\}) dx}{\int_x (\max\{u_{cheap_i}(x), u_{cheap_j}(x)\}) dx} \quad (1)$$

where $u_{\text{cheap}_i}(x)$ is USER_{*i*}'s membership function for cheap, and $u_{\text{cheap}_j}(x)$ is USER_{*j*}'s membership function for cheap.

Step 3. An agreement matrix, in Eq. (2), can be formulated when the similarity between each pair in the group is obtained (where n is the number of users)

$$AM = \begin{bmatrix} 1 & S_{12} & \cdots & S_{1j} & \cdots & S_{1n} \\ S_{21} & 1 & \vdots & \vdots & \vdots & \vdots \\ \vdots & \cdots & 1 & \vdots & \vdots & \vdots \\ S_{i1} & \cdots & \cdots & S_{ij} & \vdots & S_{in} \\ \vdots & \cdots & \cdots & \cdots & 1 & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nj} & \cdots & 1 \end{bmatrix} \quad (2)$$

where $S_{ij} = S_{ji} = S(\tilde{Q}_i, \tilde{Q}_j) = S(\tilde{Q}_j, \tilde{Q}_i)$ and if $i=j$ then $S_{ij} = 1$.

Step 4. This step calculates an average agreement degree of one single user

$$A(\text{USER}_i) = \frac{1}{n-1} \sum_{\substack{j=1 \\ i \neq j}}^n S_{ij} \quad (3)$$

Step 5. Relative Agreement Degree (RAD) for each user can be derived from the following formula

$$\text{RAD}_i = \frac{A(\text{USER}_i)}{\sum_{i=1}^n A(\text{USER}_i)} \quad (4)$$

Step 6. This step defines the weightings, w_i ($i = 1, 2, \dots, n$), for all the individuals' opinion.

Step 7. This step calculates individual Consensus Degree Coefficient (CDC) as follows

$$\text{CDC}_i = \beta w_i + (1 - \beta) \text{RAD}_i, \quad \text{where } (0 \leq \beta \leq 1) \quad (5)$$

β is used for differentiating the importance between individuals' weightings and relative agreement degrees. In our case, $\beta = 0$; as we give each individual's feedback an equal importance. Thus we can deduce that consensus degree coefficient (CDC) = relative agreement degree (RAD).

Step 8. According to the results derived from the previous step, each individual's opinion on the criterion can be gathered to form a group consensus opinion and produce Q through the following formula

$$\tilde{Q} = \sum_{i=1}^n (\text{CDC}_i \tilde{Q}_i) \quad (6)$$

Once the group consensus opinion is obtained, the (RMGDP) can be initiated to reach a consensus on their preferences over selection criteria.

3.2. Resolution method for group decision—RMGDP

The objective of RMGDP is to resolve the group differences and to reach group consensus on their preferences over selection criteria [9–13]. This method can be divided into the

following three phases: (i) transformation phase, i.e. to transform the individuals' opinions into preference values, (ii) aggregation phase, i.e. to aggregate the individual preference values for obtaining the group preference for all decision makers using OWA (Ordered Weighted Averaging) operator [14], and (iii) exploitation phase, i.e. to compute the ranking of the alternatives by group preference. These phases are detailed as follows.

3.2.1. The transformation phase

The first step of this phase is to form a collection of users as a group. Each user has to evaluate alternatives according to the defined criteria, and then assign ordering preference to the alternatives for each criterion individually. The users allocate orderings based on their own preferences and subjective judgments. A transfer function is applied to convert those individual ordering of alternatives to a preference relation, p_{ij}^k , which characterizes the ordering preference degree between alternative a_i and a_j expressed by user User_{*k*} as follows

$$p_{ij}^k = f(o_i^k, o_j^k) = \frac{1}{2} \left(1 + \frac{o_j^k}{m-1} - \frac{o_i^k}{m-1} \right) \quad (7)$$

where p_{ij}^k is a preference relation which denotes that a user User_{*k*} has a subjective ordering preference of the alternative a_i over alternative a_j and m is the number of alternatives. The transformation function, f , will satisfy that increase in o_j^k and decrease in o_i^k increases the value of p_{ij}^k . This is due to the fact that the lower ordering number represents that the user prefers the alternative, and vice versa. For instance, $O^k = \{o_1^k, o_2^k, \dots, o_m^k\}$ denotes preference ordering for User_{*k*} which prefers o_1^k to o_2^k .

3.2.2. The aggregation phase

This phase computes the collective preference, p_{ij}^c . p_{ij}^c is an aggregation of 'n users' ordering preferences $\{p_{ij}^1, \dots, p_{ij}^n\}$ which are based on the means of fuzzy majority [11]. The fuzzy majority is the product of combining the OWA (ordered weighted averaging) operator with the fuzzy quantifier. The merging function of the OWA operator and the fuzzy quantifier Q infers the collective ordering preference on each alternative as

$$p_{ij}^c = F_Q(p_{ij}^1, \dots, p_{ij}^n) = \sum_{i=1}^n w_i b_i \quad (8)$$

where $w_i = Q(in) - Q(i-1/n)$, and b_i is the i th largest value in the collection $(p_{ij}^1, \dots, p_{ij}^n)$. F_Q is the OWA operator combining the fuzzy quantifier Q to aggregate the individual preference values and to obtain the collective ordering preference of all users.

3.2.3. The exploitation phase

The exploitation phase is a consequence of identifying the priority of alternatives of group preference. In this phase, we use two well-known fuzzy ranking methods: Quantifier guided

Non-Dominance Degree (QGNDD) and Quantifier guided Dominance Degree (QGDD) [15].

The Non-Dominance Degree (NDD) of fuzzy ranking can be calculated by individual preference relation, which is formulated as follows:

$$u_{\text{NDD}} = 1 - \max\{p_{ji}^c - p_{ij}^c, 0\} \quad (9)$$

From Eq. (9), the membership function $u_{\text{NDD}}(a_i)$ can be interpreted as the degree to which a_i is not dominated by any other a_j ($j=1, \dots, m, j \neq i$), where m is the number of alternatives. The function $u_{\text{NDD}}(a_i)$ is able to find the highest ordering of alternatives. We have chosen the NDD of the alternative a_i , which is used to quantify one criterion that has a higher preference degree than all the others. For a linguistic quantifier Q (e.g. ‘most’), the NDD of the linguistic quantifier is denoted as Quantifier Guided Non-Dominance Degree (QGNDD) as

$$\text{QGNDD}(a_i) = F_Q(1 - d_{ji}^s, j = 1, \dots, m, j \neq i) = \sum_{i=1}^m w_i b_i \quad (10)$$

where $d_{ji}^s = \max\{p_{ji}^c - p_{ij}^c, 0\}$, $w_i = Q(i/m) - Q(i-1/m)$, and b_i is the i th largest value in the collection $(1 - d_{ji}^s, j = 1, \dots, m, j \neq i)$.

We recognize that the solution offered by Eq. (10) is that a fuzzy majority of the remaining alternatives a_j ($j=1, \dots, m$) does not dominate the alternative a_i . All the ordering preferences on the alternatives can be calculated by the application of Eq. (10) to prioritise their order. QGNDD cannot discriminate between the ordering of preferences, when u_{NDD} of numerous alternatives are Unfuzzy Nondominated (UND) solutions [15], i.e. $u_{\text{NDD}}(a_j) = 1$.

For instance, UND occurs when $u(a_i) \geq 0.8$, which represents the ‘most’ quantifier. In order to avoid simultaneous existences of UND solutions, the resulting fuzzy ordering needs to be validated by other fuzzy ranking methods, i.e. Quantifier Guided Dominance Degree (QGDD). According to [9], the Quantifier Guided Dominance Degree (QGDD), defined in Eq. (11), can quantify the dominance that a_i has ordering preference over all others where a_j ($j=1, \dots, m$) with the fuzzy majority concept. As a result, it is able to prioritize the final collective ordering preference. Therefore, QGDD is used to validate the fuzzy preference ordering of alternatives derived from Eq. (11) as follows

$$\text{QGDD}(a_i) = F_Q(p_{ij}^c, j = 1, \dots, m, i \neq j) \quad (11)$$

where $F_Q(a_1, a_2, \dots, a_m) = \sum_{i=1}^m w_i b_i w_i = Q(i/m) - Q(i-1/m)$, and b_i is the i th largest value in the collection (a_1, a_2, \dots, a_m) . If the ‘UND’ solutions have occurred, then we make the final preference ranking of each alternative using the results of QGDD.

4. Flight booking case study

This section illustrates the moderation processes for SAM and RMGDP through a flight-booking case study using a

composite term, called *Satisfaction*. In this case study, *Satisfaction*, which is derived from five primitive fuzzy terms, is adopted to illustrate the proposed method. This term, denoted as *Satisfaction*(\tilde{Q}), is assumed to be derived from the following primitive inference rules or fuzzy terms.

- *Cheap*. It is a measurement of the cost of flight ticket. It is denoted as *Cheap*(\tilde{Q}) or \tilde{C} .
- *DepartureTime*. It indicates the desirable (ideal) flight departure time (e.g. in minutes). It is denoted as *DepartureTime*(\tilde{Q}) or \tilde{D} .
- *ArrivalTime*. It indicates the desirable flight arrival time (in minutes). It is denoted as *ArrivalTime*(\tilde{Q}) or \tilde{A} .
- *TravelTime*. It represents the desirable duration of total travelling time. It is denoted as *TravelTime*(\tilde{Q}) or \tilde{T} .
- *Notice*. \tilde{T} is not the difference between *ArrivalTime* and *DepartureTime*.
- *Stops*. It represents the number of stops a flight has to make before reaching destination. It is denoted as *Stops*(\tilde{Q}) or \tilde{S} .

Cheap, *DepartureTime*, *TravelTime*, *ArrivalTime*, and *Stops* are initialised as follows. It is assumed that \tilde{C}_{init} (as shown in Fig. 3) is populated with an initial value and denoted as $\tilde{C}_{\text{init}} = (0, 0, 700, 1000)$, where $a \leq b \leq c \leq d$. Similarly, $\tilde{D}_{\text{init}} = (10, 11, 19, 21)$, $\tilde{T}_{\text{init}} = (0, 0, 1700, 2200)$, $\tilde{A}_{\text{init}} = (12, 13, 19, 21)$, and $\tilde{S}_{\text{init}} = (0, 0, 2, 2)$. Thus, the degree of the fuzzy term *Satisfaction*, \tilde{Q}_{init} , can be obtained by assigning them with equal weightings and adding them up:

$$\tilde{Q}_{\text{init}} = (1/5)\tilde{C}_{\text{init}} + (1/5)\tilde{D}_{\text{init}} + (1/5)\tilde{T}_{\text{init}} + (1/5)\tilde{A}_{\text{init}} + (1/5)\tilde{S}_{\text{init}}$$

Given the initial values to fuzzy terms, the inference rules can be inferred to derive the result. For instance, if the ticket price is 700 (GBP), then $\tilde{C} = \text{Cheap}(\tilde{Q}) = 1$, according to the above fuzzy rule. However, if the price is 850 (GBP), then $\tilde{C} = \text{Cheap}(\tilde{Q}) = 0.5$.

Initially, the above subjective values, \tilde{C}_{init} , \tilde{D}_{init} , \tilde{T}_{init} , \tilde{A}_{init} and \tilde{S}_{init} with uniform weightings will be used as inputs. Later, they will be replaced, respectively, by the consensus values derived from the SAM resolution process (discussed below). After the GDPs resolution process, the initial equal weightings will be modified to reflect the situation once a number of consumers’ feedbacks have been collected and calculated by the proposed method.

4.1. The SAM process

Consider a group of service consumers, User_i ($i=1, 2, 3, \dots, 30$), having different subjective opinions on the definition of term *Cheap*. In defining fuzzy queries, consumers’ feedbacks on this term can be denoted as $\tilde{C}_i(a_i, b_i, c_i, d_i)$ and formulated as the following fuzzy sets (Table 1). In this process, we have used feedback collected from 30 different consumers. For example,

Table 4
Consumers preferences for term *ArrivalTime*

$\tilde{A}_i(a_i, b_i, c_i, d_i)$			
$i=1$	(540,660,960,1080)	$i=16$	(420,540,720,840)
$i=2$	(480,600,1080,1200)	$i=17$	(660,780,840,960)
$i=3$	(540,660,960,1080)	$i=18$	(660,780,960,1080)
$i=4$	(480,600,660,780)	$i=19$	(840,960,1140,1260)
$i=5$	(780,900,1020,1140)	$i=20$	(780,900,1080,1200)
$i=6$	(480,600,840,960)	$i=21$	(720,840,1140,1260)
$i=7$	(480,600,900,1020)	$i=22$	(420,540,600,720)
$i=8$	(480,600,840,960)	$i=23$	(540,660,780,900)
$i=9$	(480,600,840,960)	$i=24$	(570,690,840,960)
$i=10$	(960,1080,1200,1320)	$i=25$	(600,720,840,960)
$i=11$	(720,840,1020,1140)	$i=26$	(900,1020,1140,1260)
$i=12$	(780,900,1080,1200)	$i=27$	(900,1020,1200,1320)
$i=13$	(660,780,900,1020)	$i=28$	(780,900,960,1080)
$i=14$	(600,720,1140,1260)	$i=29$	(420,540,600,720)
$i=15$	(420,540,660,780)	$i=30$	(900,1020,1140,1260)

Once the AM for a term *Cheap* is available, Eq. (3) is used to obtain the average agreement degree (for brevity, four users are illustrated).

$$A(\text{USER}_1) = \frac{4,046,636,820,883}{5,348,279,736,800} = 0.7566$$

$$A(\text{USER}_2) = \frac{3,530,282,949,451}{4,375,865,239,200} = 0.8068$$

⋮

$$A(\text{USER}_{29}) = \frac{912005413}{1,091,817,520} = 0.8353$$

$$A(\text{USER}_{30}) = \frac{48,244,990,777}{57,076,503,120} = 0.8453$$

of QoS term: *Cheap*.

Through Eq. (4), each individual RAD can be calculated (again, four RADs are demonstrated for brevity).

Table 5
Consumers preferences for term *Stops*

$\tilde{S}_i(a_i, b_i, c_i, d_i)$			
$i=1$	(0,0,1,2)	$i=16$	(0,0,1,2)
$i=2$	(0,0,0,1)	$i=17$	(0,0,2,3)
$i=3$	(0,0,1,2)	$i=18$	(0,0,1,2)
$i=4$	(0,0,0,1)	$i=19$	(0,0,2,3)
$i=5$	(0,0,1,2)	$i=20$	(0,0,2,3)
$i=6$	(0,0,1,2)	$i=21$	(0,0,0,1)
$i=7$	(0,0,1,2)	$i=22$	(0,0,1,2)
$i=8$	(0,0,0,1)	$i=23$	(0,0,1,2)
$i=9$	(0,0,1,2)	$i=24$	(0,0,1,2)
$i=10$	(0,0,1,2)	$i=25$	(0,0,1,2)
$i=11$	(0,0,0,1)	$i=26$	(0,0,1,2)
$i=12$	(0,0,1,2)	$i=27$	(0,0,1,2)
$i=13$	(0,0,1,2)	$i=28$	(0,0,1,2)
$i=14$	(0,0,0,1)	$i=29$	(0,0,1,2)
$i=15$	(0,0,1,2)	$i=30$	(0,0,1,2)

$$\text{RAD}_1 = 0.7566/(0.7566 + 0.8068 + 0.8353 + 0.8453) = 0.2332$$

$$\text{RAD}_2 = 0.8068/(0.7566 + 0.8068 + 0.8353 + 0.8453) = 0.2487$$

⋮

$$\text{RAD}_{29} = 0.8353/(0.7566 + 0.8068 + 0.8353 + 0.8453) = 0.2575$$

$$\text{RAD}_{30} = 0.8453/(0.7566 + 0.8068 + 0.8353 + 0.8453) = 0.2606$$

of the fuzzy term: *Cheap*

As mentioned previously, we treated each individual opinion (feedback) with equal importance, so $\beta=0$, $\text{CDC}_i = \text{RAD}_i$ (see Eq. (5)).

$$\text{CDC}_1 = \text{RAD}_1 = 0.2332$$

$$\text{CDC}_2 = \text{RAD}_2 = 0.2487$$

⋮

$$\text{CDC}_{29} = \text{RAD}_{29} = 0.2575$$

$$\text{CDC}_{30} = \text{RAD}_{30} = 0.2606$$

of QoS term: *Cheap*

Using Eq. (6), the fuzzy term: *Cheap*(\tilde{C}) can be aggregated from 30 different consumers' $\tilde{C}_i(a_i, b_i, c_i, d_i)$.

$$\tilde{C} = 0.2332\tilde{C}_1(0, 0, 450, 600)$$

$$+ 0.2487\tilde{C}_2(0, 0, 500, 650) + \dots + 0.2575\tilde{C}_{29}(0, 0, 700, 800)$$

$$+ 0.2606\tilde{C}_{30}(0, 0, 600, 700) = (0, 0, 596.1289, 778.4472)$$

Initially, a subjective value, $\tilde{C}_{\text{init}} = (0, 0, 700, 1000)$ was given to the service providers to carry out reasoning. After getting the consumers' feedbacks and opinions on the fuzzy term *Cheap*, the service consumers and providers reach a consensus. A moderated fuzzy set for fuzzy term *Cheap*, $\tilde{C} = (0, 0, 596.129, 778.447)$, is employed to replace an existing \tilde{C}_{init} . Following the same steps, we can obtain other terms *DepartureTime*, *TravelTime*, *ArrivalTime*, and *Satisfaction*:

$$\tilde{D} = (500.906, 623.325, 770.581, 890.581),$$

$$\tilde{T} = (0, 0, 1388.56, 1580.58),$$

$$\tilde{A} = (621.255, 741.255, 944.676, 1064.68),$$

$$\tilde{S} = (0, 0, 0.95, 1.95)$$

The above replace existing \tilde{D}_{init} , \tilde{T}_{init} , \tilde{A}_{init} and \tilde{S}_{init} , respectively. The fuzzy engine can use the less subjective and consensus value ($\tilde{C}, \tilde{D}, \tilde{T}, \tilde{A}, \tilde{S}$) to evolve in order to attain better effectiveness in service discovery, since they have consensus on the definition of different terms.

4.2. The RMGDP process

SAM method allows service providers and consumers to reach consensus on the definitions of primitive terms and

gain new values for these terms. However, even with the new values of \tilde{C} , \tilde{D} , \tilde{T} , \tilde{A} and \tilde{S} , the difficulty of determining the value for the composite term, *Satisfaction* (\tilde{Q}) still exists. This results in the adoption of the equal weighting assigned to \tilde{C}_{init} , \tilde{D}_{init} , \tilde{T}_{init} , \tilde{A}_{init} and \tilde{S}_{init} which are the contributing elements for the value of \tilde{Q} . Note that default weighting (equal weighing approach) may not be a realistic assignment. In order to model the composite term \tilde{Q} in a way that can be acceptable to service consumers and providers, it is essential to take their preferences into account. Thus, the service consumers have to express their preference on terms: *Cheap*, *DepartureTime*, *TravelTime*, *ArrivalTime* and *Stops*, explicitly in the order according to their importance (preference ordering). Using RMGDP, the group consensus on the importance of criteria based on their subjective preferences can be reached. The GDD and GNDD can be used to determine the weighting for each individual criterion. As a result, the composite term can be defined less subjectively.

Assume that each consumer provides their preferences on alternatives A using a preference ordering $O^k = \{o_1^k, o_2^k, \dots, o_m^k\}$ (where m is the number of alternatives). Consider that a consumer k denoted as $User_k (k=1,2,3,\dots,30)$, provides preferences on alternatives $A = \{a_1, a_2, a_3, a_4, a_5\}$, where a_1 is *Cheap*, a_2 is *DepartureTime*, a_3 is *TravelTime*, a_4 is *ArrivalTime*, and a_5 is *Stops* by the following ordering preferences $O^1 = \{a_1, a_3, a_2, a_5, a_4\}$, $O^2 = \{a_1, a_3, a_2, a_5, a_4\}$, $O^3 = \{a_1, a_5, a_3, a_2, a_4\}$ and so on. These are shown in Table 6.

For any two ordering preference values, o_i^k, o_j^k , assessed by $User_k$, a preference relation, p_{ij}^k (see Eq. (7)), shows that $User_k$ has a subjective ordering preference of the alternative a_i over alternative a_j . For each consumer, the preference ordering O^k can be transformed into fuzzy preference relation (p_{ij}^k) as follows (note that $P_{ij}^3 \sim P_{ij}^{28}$ are omitted for brevity):

Table 6
 $O^k = \{o_1^k, o_2^k, \dots, o_m^k\}$

$O^k = \{o_1^k, o_2^k, o_3^k, o_4^k, o_5^k\}$			
$k=1$	$A(1,3,2,5,4)$	$k=16$	$A(1,3,2,4,5)$
$k=2$	$A(1,3,2,5,4)$	$k=17$	$A(1,4,2,5,3)$
$k=3$	$A(1,5,3,2,4)$	$k=18$	$A(5,4,1,2,4)$
$k=4$	$A(2,5,1,3,4)$	$k=19$	$A(1,4,2,3,5)$
$k=5$	$A(3,4,5,1,2)$	$k=20$	$A(2,4,5,3,1)$
$k=6$	$A(1,3,4,5,2)$	$k=21$	$A(3,2,4,5,1)$
$k=7$	$A(1,5,3,2,4)$	$k=22$	$A(1,3,5,2,4)$
$k=8$	$A(5,3,4,2,1)$	$k=23$	$A(4,2,5,1,3)$
$k=9$	$A(1,2,3,5,4)$	$k=24$	$A(3,2,4,5,1)$
$k=10$	$A(3,2,1,4,5)$	$k=25$	$A(3,2,4,1,5)$
$k=11$	$A(1,3,2,4,5)$	$k=26$	$A(3,2,4,1,5)$
$k=12$	$A(1,3,2,4,5)$	$k=27$	$A(1,4,2,3,5)$
$k=13$	$A(2,4,3,5,1)$	$k=28$	$A(2,4,5,3,1)$
$k=14$	$A(3,4,2,5,1)$	$k=29$	$A(3,2,4,1,5)$
$k=15$	$A(1,2,4,3,5)$	$k=30$	$A(1,4,5,2,5)$

$$p_{ij}^1 = \begin{bmatrix} 0.5 & 0.75 & 0.625 & 1 & 0.875 \\ 0.25 & 0.5 & 0.375 & 0.75 & 0.625 \\ 0.375 & 0.625 & 0.5 & 0.875 & 0.75 \\ 0 & 0.25 & 0.125 & 0.5 & 0.375 \\ 0.125 & 0.375 & 0.25 & 0.625 & 0.5 \end{bmatrix},$$

$$p_{ij}^2 = \begin{bmatrix} 0.5 & 0.75 & 0.625 & 1 & 0.875 \\ 0.25 & 0.5 & 0.375 & 0.75 & 0.625 \\ 0.375 & 0.625 & 0.5 & 0.875 & 0.75 \\ 0 & 0.25 & 0.125 & 0.5 & 0.375 \\ 0.125 & 0.375 & 0.25 & 0.625 & 0.5 \end{bmatrix},$$

$$p_{ij}^{29} = \begin{bmatrix} 0.5 & 0.375 & 0.625 & 0.25 & 0.75 \\ 0.625 & 0.5 & 0.75 & 0.375 & 0.875 \\ 0.375 & 0.25 & 0.5 & 0.125 & 0.625 \\ 0.75 & 0.625 & 0.875 & 0.5 & 1 \\ 0.25 & 0.125 & 0.375 & 0 & 0.5 \end{bmatrix},$$

$$p_{ij}^{30} = \begin{bmatrix} 0.5 & 0.875 & 1 & 0.625 & 1 \\ 0.125 & 0.5 & 0.625 & 0.25 & 0.625 \\ 0 & 0.375 & 0.5 & 0.125 & 0.5 \\ 0.375 & 0.75 & 0.875 & 0.5 & 0.875 \\ 0 & 0.375 & 0.5 & 0.125 & 0.5 \end{bmatrix}$$

After transforming preference orderings into fuzzy preference relations, we can compute the collective preference relation p_{ij}^c using Eq. (8). In this case, we treat consumers' opinions on an equal basis so that the corresponding OWA operator with the weighting vector would be $w1=(1/30, 1/30, 1/30, 1/30, \dots, 1/30, 1/30, 1/30)$, $w2=(1/4, 1/4, 1/4, 1/4)$, and the p_{ij}^c is as follows:

$$p_{ij}^c = \begin{bmatrix} 0.5 & 0.65 & 0.6417 & 0.6458 & 0.6792 \\ 0.35 & 0.5 & 0.4917 & 0.4958 & 0.5292 \\ 0.3583 & 0.5083 & 0.5 & 0.5042 & 0.5375 \\ 0.3542 & 0.5042 & 0.4958 & 0.5 & 0.5333 \\ 0.3208 & 0.4708 & 0.4625 & 0.4667 & 0.5 \end{bmatrix}$$

Moreover, the Quantifier Guided Dominance Degree (QGDD) and Quantifier Guided Non-Dominance Degree (QGNDD) could be obtained using Eqs. (10) and (11). The level of three alternatives importance is evidently identified through the application of QGDD and QGNDD. This result is shown in Table 7. It is interesting to note that both QGDD and QGNDD have drawn the same conclusion that is, $a_1(\text{Cheap}) > a_3(\text{TravelTime}) > a_4(\text{ArrivalTime}) > a_2(\text{DepartureTime}) > a_5(\text{Stops})$. This is shown in Figs. 4 and 5.

In addition to identifying preference orderings, the value of QGDD and QGNDD can also be used to calculate the weights for each alternative. The consensus weightings for alternatives

Table 7
QGDD and QGNDD for alternatives and the consensus weights for alternatives

QGDD for alternatives	a_1 (<i>Cheap</i>) 0.6542	a_2 (<i>DepartureTime</i>) 0.4667	a_3 (<i>TravelTime</i>) 0.4771	a_4 (<i>ArrivalTime</i>) 0.4719	a_5 (<i>Stops</i>) 0.4302
QGNDD for alternatives	a_1 (<i>Cheap</i>) 1	a_2 (<i>DepartureTime</i>) 0.9188	a_3 (<i>TravelTime</i>) 0.9292	a_4 (<i>ArrivalTime</i>) 0.9250	a_5 (<i>Stops</i>) 0.8604
Consensus weights for alternatives from QGDD	wa_1 (<i>Cheap</i>) 0.2617	wa_2 (<i>DepartureTime</i>) 0.1867	wa_3 (<i>TravelTime</i>) 0.1908	wa_4 (<i>ArrivalTime</i>) 0.1888	wa_5 (<i>Stops</i>) 0.172
Consensus weights for alternatives from QGNDD	wa_1 (<i>Cheap</i>) 0.2158	wa_2 (<i>DepartureTime</i>) 0.1983	wa_3 (<i>TravelTime</i>) 0.2006	wa_4 (<i>ArrivalTime</i>) 0.1996	wa_5 (<i>Stops</i>) 0.1857

that are derived from QGDD and QGNDD are given by $W=(0.2617, 0.1867, 0.1908, 0.1888, 0.172)$ and $W=(0.2158, 0.1983, 0.2006, 0.1996, 0.1857)$. That is, the consensus weights for the fuzzy term: *Cheap* is 0.2617 (derived from QGDD). Finally, the fuzzy term, *Satisfaction* can be moderated as:

$$\tilde{Q} = 0.2617\tilde{C} + 0.1867\tilde{D} + 0.1908\tilde{T} + 0.1888\tilde{A} + 0.172\tilde{S}$$

5. Validation

This section describes the evaluation of the proposed approach. The evaluation is based on a case study that comprises 30 different service consumers and nine different airlines services of different service providers. In the following, we evaluate the proposed Moderated Fuzzy Discovery Method (MFDM) in comparison to Capability Discovery Method (CDM) and Fuzzy Discovery Method (FDM).

5.1. Capability discovery method (CDM)

The CDM method is a service discovery approach, which adopts the function or capability of the service as a only criterion for matchmaking. In the first set of experiments, we use CDM without involving FDM. In this method, the capability matchmaker suggests all the nine web services to the consumers, as they satisfy the requirements in terms of capability constraints. This method is therefore inappropriate as each consumer has to interrogate the data repositories of web services in order to discover the required service. Table 8 shows these results. The fuzzy set for consumer 1, for example, is represented as follows:

$$\tilde{C}_1(a_1, b_1, c_1, d_1) = (0, 0, 450, 600),$$

$$\tilde{D}_1(a_1, b_1, c_1, d_1) = (540, 660, 960, 1080),$$

$$\tilde{T}_1(a_1, b_1, c_1, d_1) = (0, 0, 1350, 1590),$$

$$\tilde{A}_1(a_1, b_1, c_1, d_1) = (540, 660, 960, 1080),$$

$$\tilde{S}_1(a_1, b_1, c_1, d_1) = (0, 0, 1, 2)$$

$\tilde{C}_1(a_1, b_1, c_1, d_1) = (0, 0, 450, 600)$ means that consumer 1 has a subjective opinion on the price for a cheap flight (between 0 and 600 GBP). Thus only five airline web services can meet consumer 1’s requirements. So the precision rate is 55.66% ($5/9=0.5556$). The same principle can be applied to other service consumers in order to evaluate the precision rates. Table 8 shows the derived precision rates 0.5556, 0.3333, 0.5556, and 0.4444 for the consumers 1, 2, 29, 30, respectively.

5.2. Fuzzy discovery method (FDM)

The second set of experiments is carried out for testing the FDM. FDM was deployed after the service providers have conducted fuzzy classification on the data. Thus, the initial composite inference rule, $\tilde{Q}_{init} = 0.2\tilde{C}_{init} + 0.2\tilde{D}_{init} + 0.2\tilde{T}_{init} + 0.2\tilde{A}_{init} + 0.2\tilde{S}_{init}$ is introduced to calculate QoS term: *Satisfaction* for each service provider. The classification results are shown in Table 9.

Suppose that the threshold $\theta=0.45$ is adopted for all web consumers. θ is subjectively defined by the service consumers ability to filter out those services that have less possibility than the threshold value for meeting the requirements. In this case, the

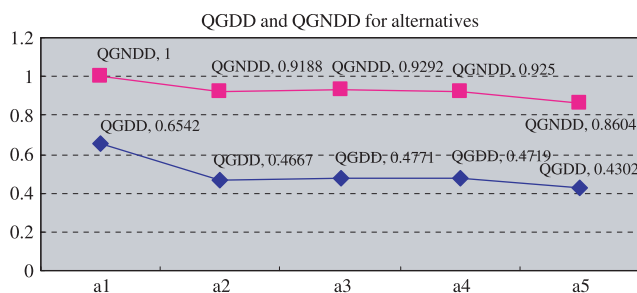


Fig. 4. QGDD and QGNDD for alternatives.

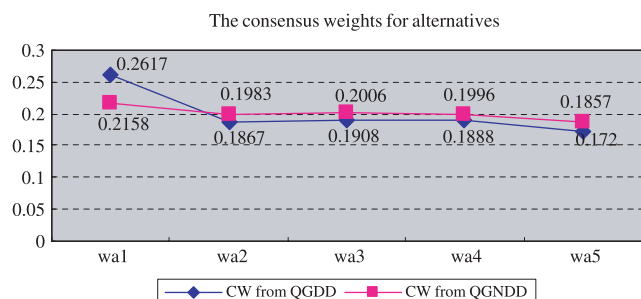


Fig. 5. The consensus weights (CW) for alternatives.

Table 8
CDM precision rates for consumers 1, 2, 29, and 30

CDM suggestions (no. of filtering)	C1	C2	...	C29	C30
AlitaliaAir	✓		...	✓	
BritishAir			...		
Cathay PacificAir	✓	✓	...	✓	✓
EvaAir			...		✓
KlmRoyal DutchAir	✓		...	✓	✓
KoreanAir			...		
MalaysianAir			...		
SingaporeAir	✓	✓	...	✓	✓
ThaiAir	✓	✓	...	✓	
Precision rate for specific consumer	5/9=0.5556	3/9=0.3333	...	5/9=0.5556	4/9=0.4444

Table 9
Values for the fuzzy term Satisfaction using \tilde{Q}_{init} with equal weight

AirLine	Fuzzy value for satisfaction	AirLine	Fuzzy value for satisfaction
AlitaliaAir	0.6*	KoreanAir	0.5*
BritishAir	0.76*	MalaysianAir	0.86*
Cathay PacificAir	0.8*	SingaporeAir	0.82*
EvaAir	0.65*	ThaiAir	0.65*
KimRoyal DutchAir	0.83*		*Added when fuzzy value $\geq \theta$

fuzzy discovery recommends nine possible satisfactory web services. From the information presented in Tables 1–5, consumer 2 has the following preferences for the fuzzy term Satisfaction:

$$\tilde{C}_2(a_2, b_2, c_2, d_2) = (0, 0, 500, 650),$$

$$\tilde{D}_2(a_2, b_2, c_2, d_2) = (420, 540, 900, 1020),$$

$$\tilde{T}_2(a_2, b_2, c_2, d_2) = (0, 0, 1170, 1470),$$

$$\tilde{A}_2(a_2, b_2, c_2, d_2) = (480, 600, 1080, 1200),$$

$$\tilde{S}_2(a_2, b_2, c_2, d_2) = (0, 0, 0, 1)$$

$\tilde{C}_2(a_2, b_2, c_2, d_2) = (0, 0, 500, 650)$ indicates that consumer 2’s subjective opinion on: Cheap price lies between 0 and 650 GBP, TravelTime lies between 0 and 1470 min, and Stops is between 0

and 1 stop. Thus, only three airline web services can satisfy this consumer’s requirements. For the consumer 2, the precision rate is 33.33% (3/9=0.3333). The same principle is applicable to other consumers. Table 10 illustrates that consumers 1, 2, 29 and 30 gain values of 55.56, 33.33, 55.56, and 44.44, respectively, for their precision rates.

5.3. Moderated fuzzy discovery method (MFDM)

The third set of experiments is conducted for testing MFDM. These experiments first employ SAM and then employ RMGDP (Parts 1 & 2 of MFDM, Section 3). SAM is used to aggregate the group consensus on the fuzzy term Satisfaction.

This produces a less subjective inference rule. That is,

$$\tilde{Q} = 0.2\tilde{C} + 0.2\tilde{D} + 0.2\tilde{T} + 0.2\tilde{A} + 0.2\tilde{S}$$

Table 10
FDM precision rates for consumers 1–4 under $\theta=0.45$

$\theta=0.45$, FDM suggestions	C1	C2	...	C29	C30
AlitaliaAir	✓		...	✓	
BritishAir			...		
Cathay PacificAir	✓	✓	...	✓	✓
EvaAir			...		✓
KlmRoyal DutchAir	✓		...	✓	✓
KoreanAir			...		
MalaysianAir			...		
SingaporeAir	✓	✓	...	✓	✓
ThaiAir	✓	✓	...	✓	
Precision rate for specific consumer	5/9=0.5556	3/9=0.3333	...	5/9=0.5556	4/9=0.4444

Table 11
Value for the fuzzy term *Satisfaction* under moderated \tilde{Q} with equal weight

AirLine	Fuzzy value for satisfaction	AirLine	Fuzzy value for satisfaction
AlitaliaAir	0.45*	KoreanAir	0.36*
BritishAir	0.48*	MalaysianAir	0.59*
Cathay PacificAir	0.71*	SingaporeAir	0.57*
EvaAir	0.58*	ThaiAir	0.52*
KimRoyal DutchAir	0.25*	*Added when fuzzy value $\geq \theta$	

Table 12
MFDM precision rates for consumers 1–4 under $\theta=0.45$ (with equal weights)

$\theta=0.45$, MFDM (equal weights) suggestions	C1	C2	...	C29	C30
AlitaliaAir	✓		...	✓	
BritishAir			...		
Cathay PacificAir	✓	✓	...	✓	✓
EvaAir			...		✓
MalaysianAir			...		
SingaporeAir	✓	✓	...	✓	✓
ThaiAir	✓	✓	...	✓	
Precision rate for specific consumer	4/7=0.5714	3/7=0.4286	...	4/7=0.5714	3/7=0.4286

where

$$\begin{aligned} \tilde{C} &= (0, 0, 596.129, 778.447), & \tilde{C}_{29}(a_{29}, b_{29}, c_{29}, d_{29}) &= (0, 0, 700, 800), \\ \tilde{D} &= (500.906, 623.325, 770.581, 890.581), & \tilde{D}_{29}(a_{29}, b_{29}, c_{29}, d_{29}) &= (540, 660, 720, 840), \\ \tilde{T} &= (0, 0, 1388.56, 1580.58), & \tilde{T}_{29}(a_{29}, b_{29}, c_{29}, d_{29}) &= (0, 0, 1470, 1710), \\ \tilde{A} &= (621.255, 741.255, 944.676, 1064.68), & \tilde{A}_{29}(a_{29}, b_{29}, c_{29}, d_{29}) &= (420, 540, 600, 720), \\ \tilde{S} &= (0, 0, 0.95, 1.95) & \tilde{S}_{29}(a_{29}, b_{29}, c_{29}, d_{29}) &= (0, 0, 1, 2) \end{aligned}$$

With the new derived inference rules, the fuzzy classifier can be employed for fuzzy classification in order to obtain new fuzzy value for QoS term: *Satisfaction*. This is illustrated in Table 11.

In this instance, $\theta=0.45$ is adopted and only seven airline web services are discovery satisfactorily (AlitaliaAir, BritishAir, CathayPacificAir, EvaAir, MalaysianAir, SingaporeAir, and ThaiAir). According to Tables 1–5, consumer 29 has following subjective opinion for QoS term, *Satisfaction*:

The above reveals that consumer 29 has a subjective opinion on: *Cheap* price which sits between 0 and 800 GBP, *TravelTime* which lies between 0 and 1710 min, and *Stops* rests between 0 and 2 stops. So, only four airline web services can satisfy his/her opinion. However, the precision rate has increased to 57.14% (4/7=0.5714), due to the contribution of moderation. Table 12 shows the service consumers 1, 2, 29 and 30 obtain their precision rates 57.14, 42.86, 57.14 and 42.86%, respectively, by employing the MFDM.

After the completion of SAM process, RMGDP process is applied to acquire the consensus weightings for the predefined five criteria. Therefore, the QoS term *Satisfaction* with

Table 13
Value for the term: *Satisfaction* with consensus weights (\tilde{Q})

AirLine	Value for satisfaction	AirLine	Value for satisfaction
AlitaliaAir	0.5*	KoreanAir	0.38
BritishAir	0.44	MalaysianAir	0.61*
Cathay PacificAir	0.72*	SingaporeAir	0.58*
EvaAir	0.6*	ThaiAir	0.49*
KlmRoyal DutchAir	0.29	*Added when QoS value $\geq \theta$	

Table 14
MFDM precision rates for consumers 1–4 under $\theta=0.45$ (with consensus weights)

$\theta=0.45$, MFDM (equal weights) suggestions	C1	C2	...	C29	C30
AlitaliaAir	✓		...	✓	
Cathay PacificAir	✓	✓	...	✓	✓
EvaAir			...		✓
MalaysianAir			...		
SingaporeAir	✓	✓	...	✓	✓
ThaiAir	✓	✓	...	✓	
Precision rate for specific consumer	4/6=0.6667	3/6=0.5	...	4/6=0.6667	3/6=0.5

Table 15
Average precision rate for CDM, FDM and MFDM under θ is 0.45

Precision rate for specific consumer	No. of Sug.	C1	C2	...	C29	C30	Average precision rate
CDM	9	0.5556	0.3333	...	0.5556	0.4444	0.3926
FDM	9	0.5556	0.3333	...	0.5556	0.4444	0.3926
MFDM (equal weights)	7	0.5714	0.4286	...	0.5714	0.4286	0.4476
MFDM (consensus weights)	6	0.6667	0.5	...	0.6667	0.5	0.5167

consensus weightings is employed for fuzzy classification in order to obtain new fuzzy value for QoS term *Satisfaction*.

$$\tilde{Q} = 0.2617\tilde{C} + 0.1867\tilde{D} + 0.1908\tilde{T} + 0.1888\tilde{A} + 0.172\tilde{S}$$

Table 13 illustrates the above value \tilde{Q} .

If $\theta=0.45$ is adopted, only six airline web services (AlitaliaAir, CathayPacificAir, EvaAir, MalaysianAir, SingaporeAir, and ThaiAir) are able to meet the requirements. Based on the information from Tables 1 to 5, the consumer 30 has inference rules for QoS term *Satisfaction* as follows:

$$\tilde{C}_{30}(a_{30}, b_{30}, c_{30}, d_{30}) = (0, 0, 600, 700),$$

$$\tilde{D}_{30}(a_{30}, b_{30}, c_{30}, d_{30}) = (900, 1020, 1140, 1260),$$

$$\tilde{T}_{30}(a_{30}, b_{30}, c_{30}, d_{30}) = (0, 0, 1410, 1650),$$

$$\tilde{A}_{30}(a_{30}, b_{30}, c_{30}, d_{30}) = (900, 1020, 1140, 1260),$$

$$\tilde{S}_{30}(a_{30}, b_{30}, c_{30}, d_{30}) = (0, 0, 1, 2)$$

It shows that the consumer-30 subjective: *Cheap* price sits between 0 and 700 GBP, *TravelTime* lies between 0 and 1650 min, and *Stops* is between 0 and 2 stops. Thus, only three

airline web services can satisfy the consumer-30 subjective opinion. However, the precision rate has increased to 50% (3/6=0.5). Applying the same steps to the other service consumers 1, 2, and 29, we can obtain their precision rates as 57.14, 42.86, 57.14 and 42.86%, respectively. These are shown in Table 14.

Table 15 shows an integrated view of Tables 8, 10, 12, and 14. It shows the average precision rates for Capability Discovery Method, Fuzzy Discovery Method, Moderated fuzzy Discovery Method (with equal weights) and Moderated Fuzzy Discovery Method (with consensus weights).

From Table 15, it is observed that the proposed MFDM has outperformed CDM and FDM. With a derived consensus weighting, it also produces better precision rate (i.e. 12.41%) than the other two methods. Note that the average precision rate for FDM is identical to the rate for CDM. This is because both, FDM and CDM have the same number of recommended web services when $\theta=0.45$.

The average precision rates shown in Tables 16 and 17 suggest that MFDM is able to produce better results than CDM and FDM when θ is 0.5 or 0.55. Thus, MFDM has produced a higher precision rate than CDM by 6–16% and FDM by 3–16%. Though these may seem insignificant, the number of

Table 16
Average precision rate for CDM, FDM and MFDM under θ is 0.5

Precision rate for specific consumer	No. of Sug.	C1	C2	...	C29	C30	Average precision rate
CDM	9	0.5556	0.3333	...	0.5556	0.4444	0.3926
FDM	9	0.5556	0.3333	...	0.5556	0.4444	0.3926
MFDM (equal weights)	5	0.6	0.6	...	0.6	0.8	0.5533
MFDM (consensus weights)	5	0.6	0.4	...	0.6	0.6	0.453

Table 17
A precision rate for CDM, FDM and MFDM under θ is 0.55

Precision rate for specific consumer	No. of Sug.	C1	C2	...	C29	C30	Average precision rate
CDM	9	0.5556	0.3333	...	0.5556	0.4444	0.3926
FDM	8	0.625	0.375	...	0.625	0.5	0.4417
MFDM (equal weights)	4	0.5	0.5	...	0.5	0.75	0.475
MFDM (consensus weights)	4	0.5	0.5	...	0.5	0.75	0.475

recommended web services is significantly reduced (by 50%). In other words, with the provision of MFDM, service consumers are able to eliminate unnecessary searching and increase the precision rate of locating the required services.

When $\theta=0$, it means that the service consumers' threshold is not considered in the discovery process. Instead, the discovery mechanism only suggests those services that best match the consumers' requirements. In other words, the discovery mechanism only highlights those services with the most significant satisfaction values. Under this scenario, FDM proposed airline KlmRoyalDutchAir (satisfaction value 0.83), MFDM (with equal weightings) recommended airline CathayPacificAir (satisfaction value 0.68) and MFDM (with consensus weightings) suggested airline CathayPacificAir (satisfaction value 0.69). Table 18 shows that the average precision rate has dramatically increased to 90%. This resulted from the effectiveness of moderation process.

6. Discussion

The above experimental results demonstrate that the proposed Moderated Fuzzy Discovery Method (MFDM) effectively discover required web services. This method is built upon an assumption that participating service consumers and providers have inconsistent views on the terms they use in the service discovery. We believe that this is a rational proposition, since their expectations and perceptions vary greatly due to their experiences, preferences and knowledge. These inconsistent views on the services greatly complicate the process of service discovery. The traditional ontological technology [16] resolves inconsistency on the definitions of terms. However, it cannot be applied to a dynamic environment.

There exist a number of service discovery mechanisms [17–19] based on non-functional criteria to select appropriate services from a set of overlapping services which provide similar or identical functions. From the experimental results,

we believed that this method is complementary to them as it introduces another dimension (contents of services) to the web service discovery. In addition, the proposed approach provides a consensus reaching mechanism to bridge the gaps between the different expectations and preferences of service providers and consumers.

Further [20] reports on the comparison of different algorithms such as naive algorithm, Fagin's algorithm, and threshold algorithm. These algorithms aggregate information from various data sources. The aim is to retrieve overall top-k objects from data resources [19] presents an approach for answering imprecise queries in web-accessible databases. This approach is claimed to enable databases to support imprecise queries by identifying a set of related precise queries which return the results that are more relevant to the user's queries. This approach is somewhat relevant to our approach. The above approaches [20,21] do not consider the consensus aspects nor they consider web services.

In the proposed approach, there exist some unresolved issues which we plan to address in future. We have assumed that the users will change their opinions and preferences in line with the consensus. This may not be the case when users have strong opinions and preferences. We have also assumed that there is no dependency among the selection criteria, which in some cases may not be realistic. This requires a sophisticated negotiation system to be in place in order to resolve these issues.

7. Summary

In this paper, a novel moderated fuzzy web service discovery mechanism is presented. It allows web service providers and consumers to reach consensus on contents of services, even though they have different opinions and preferences on the terms they use. The proposed method employs SAM and RMGDP. SAM method is used to resolve users' differences on definitions of the primitive fuzzy terms, while RMGDP is used to eliminate their differences in opinions and preferences on the composite

Table 18
Average precision rate for CDM, FDM and MFDM with best choice

Precision rate for specific consumer	No. of Sug.	C1	C2	...	C29	C30	Average precision rate
CDM	9	0.5556	0.3333	...	0.5556	0.4444	0.3926
FDM	1	0	0	...	0	0	0
MFDM (equal weights)	1	1	1	...	1	1	0.9
MFDM (consensus weights)	1	1	1	...	1	1	0.9

fuzzy terms. The proposed method was implemented and a number of experiments were carried out based on a flight booking case study. The experiments demonstrated that the proposed method outperforms capability based and traditional fuzzy discovery methods.

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