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Multicriteria Decision Making with Fuzziness and Criteria Interdependence in Cloud Service Selection

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***Abstract*—With the advent of Cloud computing and subsequent big data, online decision makers usually find it difficult to make informed decisions because of the great amount of irrelevant, uncertain, or inaccurate information. In this paper, we explore the application of multicriteria decision-making (MCDM) techniques in the area of Cloud computing and big data, to find an efficient way of dealing with criteria relations and fuzzy knowledge based on a great deal of information. We propose a MCDM framework, which combines the ISM-based and ANP-based techniques, to model the interactive relations between evaluation criteria, and to handle data uncertainties. We present an application of Cloud service selection to prove the efficiency of the proposed framework, in which a user-oriented sigmoid utility function is designed to evaluate the performance of each criterion.**

Keywords—Cloud service selection; quality of service; criteria interdependence; MCDM; fuzzy integral

I. INTRODUCTION

Multicriteria decision making (MCDM) techniques have been developed and applied in a wide range of areas such as decision support systems, objective optimization, performance simulation, etc. MCDM has attracted a great deal of attention, and there has been an increased focus on addressing new issues arising in the IT area, particularly the capability of dealing with big data [1], and the decision modeling in Cloud environment [2]. The applications in both of these areas require more advanced techniques for data collection, classification, analysis, and more comprehensive and interactive data evaluation.

The classical MCDM techniques assume that the criteria used for alternative evaluation are independent of each other [3]. To achieve this, they require minimizing the number of criteria, avoiding the abundant criteria, and omitting the conflicting relationship between conflicting criteria. This assumption may cause significant information loss and imprecise evaluation of alternatives. As stated by [4], everything can influence everything else, even itself, in terms of a variety of criteria, and the world is far more interdependent compared with the ways in which we think and act. In recent years, research has focused on considering the inter-relationship between criteria, which requires non-additive utility aggregation techniques [5], and is more adaptive to the real applications.

There are usually three types of inter-relationships between criteria—supportive, conflicting, and independent [6]. Supportive (also called abundant, negative, etc.) criteria are those with similar meanings and functions (e.g., speed and acceleration of a car), which can influence each other's performance positively, but their coalition may affect the valuation of an alternative negatively. Conflicting (also called positive, synergic, etc.) criteria are of the opposite meaning. They influence each other's performance negatively, but their interaction can bring positive influence on the alternative valuation, e.g., acceleration and cost of a car. There is no relation between independent criteria. The influence of their combination on the alternative is additive without considering their interaction degrees.

As mentioned previously, vagueness of expression and data uncertainty are two issues usually faced by decision makers. Service-related expressions (e.g., service descriptions, business objectives, and user preference) often employ natural languages, which obscure the boundaries of data classification and make it difficult quantify and compare. The capability of modeling uncertainty is essential for a decision system to capture the unquantified fuzziness and to improve the accuracy of decision making. Linguistic variables [7] were proposed to deal with the vagueness in natural languages, and are typically applied to solve problems with fuzziness.

This research explores the application of MCDM techniques in the service-oriented environment, and gives a detailed example of applying the proposed framework to Cloud service selection problems. The framework consists of three components: an interactive interpretive structure modeling (I-ISM) process, an interactive fuzzy analytic network process (IF-ANP), and a non-additive utility integral procedure—2-order additive fuzzy integral. The I-ISM is an extension of the traditional interpretive structure modeling (ISM) approach. It integrates the definition of types of relations with the traditional single influence relations, and helps to identify the different types of potential transitive relations. A set of relational logic operations and an interactive adjustment process are established in order to identify the transitive relations. On the other hand, I-ISM still has the noticeable deficiency characteristic of the traditional ISM—it cannot help to deduce the interaction weights of a relation [8]. This work proposes a fuzzy analytic network process (FANP)-based model as a supplement of ISM to determine the interaction importance.

Like the statement in [9], the output of ISM can be a satisfactory input to the analytic network process (ANP), and produces a more usable outcome than the results of only using any one of them. The FANP technique has been studied by many researchers due to its significance and applicability. One of the deficiencies of the existing FANP technique, however, is that it does not distinguish the types of criteria relations (e.g., conflicting or supportive). Most of the work assumes that all the criteria involved are conflicting with each other. In addition, they usually only consider the weight of singleton, which will be aggregated by a simple weighted aggregation operator in utility calculations. Whereas, the interaction weight between a pair of interactive criteria can also dramatically influence the overall utilities. To address the deficiencies, we propose to record the types of criteria relations in an ANP network, and to identify the interactive importance of pairs of criteria using pair-wise comparisons. The proposed IF-ANP inherits the features and functions of ANP that is therefore capable of compiling all the relevant criteria and capturing their interrelationships to arrive at rational decisions [10]. Moreover, IF-ANP supports both the modeling of types of criteria relations and the information fuzziness, which is constructed from the I-ISM structure. The importance of the interaction between different types of criteria can be deduced by combining the traditional ANP inference process with the definition of relation types, which helps to produce a fuzzy measure to integrate the non-additive marginal criteria utilities. The 2-order additive fuzzy integral is used to integrate the non-additive utilities. This has been chosen because, in a real MCDM scenario, the interaction between a pair of criteria is sufficient for decision making, and it is very difficult and even meaningless to evaluate the interactive degree of three or more criteria [6].

The structure of the paper is as follows: Section II introduces the related work and background information. Section III describes the I-ISM model and related operations. Section IV shows how to process the IF-ANP. A case study of Cloud service selection is given in Section V, including a comparative analysis of the results. Section VI concludes this paper.

II. Literature Review and Background Information

A. Analytic Network Process

ANP is a generalization of an analytic hierarchic process (AHP) [11]. It is structured as a network that compiles the contextual elements and domain knowledge. The network structure supports the modeling of the interactive relations among criteria, and of the feedback influence from alternatives to criteria. Both AHP and ANP were widely applied in different decision-making fields [12]-[14]. Interested readers can refer to [11] for the detailed introduction of ANP and AHP.

B. 2-order Additive Choquet Integral

A fuzzy integral is a kind of utility aggregating operator that is capable of measuring the influence of the importance of a criterion and the importance of interactions among criteria [15]. A set of importance values needs to be defined to calculate the fuzzy integral, that is, a set of importance values for all the subsets of a set of elements (e.g., decision criteria, a group of players in a game, etc.). The importance-value set is called a fuzzy measure. Therefore, the critical step of applying a fuzzy integral successfully is to define a fuzzy measure very precisely.

Though the fuzzy integral shows more rationality and richness compared with the additive measures (e.g., simple weighted additive, SWA), it has not been well received in terms of its practical application due to its difficulty and complexity when used to identify the unobvious fuzzy measures [16]. To address this kind of complexity, efforts have been made consistently during the past decades, with several approaches being proposed such as the λ-measure fuzzy integral [17], k-order additive fuzzy measure [16] etc.. In particular, the k-order additive fuzzy measure provides an intermediate solution between the simple additive measures and the general cases. In real applications, the weight of a singleton criterion and the interaction weight between a pair of criteria are worthy of consideration by decision makers, while it is very difficult for them to give the same importance to the interaction among three or more criteria. Therefore, the 2-additive fuzzy measure can be handled more easily (only n(n+1)/2 parameters need to be identified in terms of Mobius representation [18]) and is of enough rationale compared with the case of k>2 [6]. This work will utilize the 2-additive fuzzy measure with respect to non-monotonic set functions. The details regarding the basic definitions and properties of the 2-additive fuzzy measure can be referred from [19].

C. Linguistic Variables

The theory of linguistic variables is proposed to handle the situation that is too complex to be reasonably expressed or defined. Linguistic variables are used to represent the uncertainties in human cognition [20]. Five triangular linguistic terms are defined corresponding to five level scales of criterion importance: *absolutely important*, *very strongly important*, *essentially important*, *weakly important*, and *equally important* [21], which are shown in Table I.

The technique of α-cut defuzzification is adopted to defuzzify the fuzzy pair-wise comparison matrixes formed by the linguistic variables. An α-cut confidence interval with respect to a triangular fuzzy number $\tilde{v} = [l, m, u]$ is defined as: $\forall \alpha \in [0,1], \tilde{m} = [n_l^\alpha, n_u^\alpha] = [(m-l)\alpha + l, -(u-m)\alpha + u]$, where α value is determined by the decision maker, based on its confidence level on the vague judgments [22]. Other than the confidence level, the satisfaction degree should also be determined to determine the crisp evaluation value, which is achieved by the index of optimism μ as: $a_{ij}^\alpha = \mu a_{iju}^\alpha + (1-\mu) a_{ijl}^\alpha, \forall \mu \in [0,1]$. The larger the index μ, the higher the optimism degree [22].

The next section will introduce the proposed framework. An example of Cloud storage service selection with various criteria will be used as an example throughout the later description to show the operation of the framework. Assume there are n alternatives to a Cloud storage service. The service is evaluated according to nine criteria: *availability* (*av*), *reliability* (*re*), *scalability* (*sc*), *storage capacity* (*stc*), *data transfer speed* (*dts*), *latency* (*la*), *types of customer support* (*tcs*), *response speed of customer support* (*rscs*), and *cost* (*co*).

TABLE I. LINGUISTIC VARIABLES FOR CRITERIA INTERDEPENDENCE EVALUATION

Linguistic Variable	**Triangular Fuzzy Number**
absolutely important	(7,9,9)
very strongly important	(5,7,9)
essentially important	(3,5,7)
weakly important	(1,3,5)
equally important	(1,1,3)

III. NETWORK CONSTRUCTION BASED ON INTERACTIVE ISM

An improved ISM approach, namely Interactive Interpretive Structural Modeling (I-ISM), is proposed to help to establish the network of criteria relations, which will be an input of the subsequent ANP process.

Typically, four types of *leads to* relations are modeled by an ISM, distinguished by the direction of a relation between two criteria (e.g., criteria *i* and *j*): 1) *i* influence *j*; 2) *j* influence *i*; 3) mutual influence between *i* and *j*; and 4) *i* independent with *j*. We continue using the four directions of *influence* relation to form the initial relation matrix (i.e., a matrix includes only direct relations that are easily assigned manually). Furthermore, we propose to integrate the supportive and conflicting characteristics of relations into the ISM in order to present a clear picture of the types of criteria relations, and to facilitate the identification of fuzzy measures in the ANP-based inference stage. On the other hand, the definition and analysis of conflicting and supportive criteria relations in [23] indicates that specific to the area of multicriteria decision making, a relation between a couple of criteria is usually symmetric, that is, if criteria *i* and *j* are supportive (or conflicting), then the increase of the performance of *i* can lead to the increase (or decrease) of the performance of *j*, and vice versa. Therefore, it is reasonable to assume that the final stable criteria relational structure (i.e., the reachability matrix) is symmetric. A definition of *matrix consistency* is established to ensure the symmetry of relations.

Details for building I-ISM models and constructing corresponding ANP networks will be given later. We first introduce some basic definitions and operations used in I-ISM. Let $C = \{c_1, c_2, ..., c_n\}$ a set of criteria, $F = \{f_1, f_2, ..., f_n\}$ the performance of the criteria. For any $c_i, c_j \in C$, there are five interactive relations: if $f_i \uparrow \Rightarrow f_j \uparrow$, then c_i supports c_j; if $f_i \uparrow \Leftrightarrow f_j \uparrow$, then c_i is supportive with c_j. If $f_i \downarrow (resp. \uparrow) \Rightarrow f_j \uparrow (resp. \downarrow)$, then c_i opposes c_j; if $f_i \downarrow (resp. \uparrow) \Leftrightarrow f_j \uparrow (resp. \downarrow)$, then c_i is conflicting with c_j. Otherwise, they are independent of each other. A relation is *supportive with* itself. The relations that *support* and *oppose* are **asymmetric** relations; while *supportive with*, *conflicting with*, and *independent with* are **symmetric** relations. The relations *support* and *supportive with* satisfy $f(\{c_i, c_j\}) < f_i + f_j$, and are called negative relations; the relations *oppose* and *conflicting with* satisfy $f(\{c_i, c_j\}) > f_i + f_j$, and are called positive relations; and the relation *independent with* satisfies $f(\{c_i, c_j\}) = f_i + f_j$, and is called an additive relation.

A **'-1~0~1' relation value** is a value $r_{ij} \in \{-1, 0, 1\}$, indicating an interactive relation between c_i and c_j. $c_i(r_{ij})c_j$ represents a *symmetric* relation, and $c_i[r_{ij})c_j$ stands for an *asymmetric* relation, meaning that c_i influences c_j in the relation r_{ij}. In particular, r_{ij}=-1 refers to a *negative* relation, r_{ij}=1 represents a *positive* relation, and r_{ij}=0 means an *additive* relation. If c_i interacts with c_j via other criteria, then their relation is a **transitive** relation, represented by r_{ij}^*, or r_{ij}^k, where $k \geq 1$ is the number of criteria in-between c_i and c_j. If k=0, then the relation is a **direct** relation, represented by r_{ij}^0. If there is no special statement, we use r_{ij} to represent either transitive or direct relation. If c_i interacts with c_j, then there is at least one relation path from c_i to c_j. A **relation path** is a directed path with c_i as the head and c_j as the tail, comprising a directed criteria sequence (with k criteria c_1,..,c_k, $k \geq 0$) in-between. It can be represented as $p_{ij} = \{r_{i1}^0 \cap r_{12}^0 \cap ... \cap r_{kj}^0\}$.There may be m paths from c_i to c_j, $m > 0$, represented by $P_{ij} = \{r_{ij1} \cup r_{ij2} \cup ... \cup r_{ijm}\}$. If m=0, then c_i and c_j are independent with each other.

To operate the relations (i.e., the '-1~0~1' values) and to identify a transitive relation, we define two context-aware logical operators 'logic addiction ($\overline{\vee}$)'and 'logic multiplication ($\overline{\wedge}$)'.

Assume that there are m parallel relation paths from c_i to c_j, **logic addition** ($\overline{\vee}$) is used to aggregate the m paths to decide the relation from c_i to c_j. It has the following properties:

1) if $\forall r_{ij} = 0$, then $r_{ij1} \overline{\vee} r_{ij2} \overline{\vee} \cdots \overline{\vee} r_{ijm} = 0$.
2) if $\exists r_{ijp} = 1 \ (resp. -1)$, and $\nexists r_{ijq} = -1 \ (resp. 1)$, $p, q \in \{1, ..., m\}$, then $r_{ij1} \overline{\vee} r_{ij2} \overline{\vee} \cdots \overline{\vee} r_{ijm} = 1 \ (resp. -1)$.
3) if $\exists r_{ijp} = 1$ and $\exists r_{ijq} = -1$, then $r_{ij1} \overline{\vee} r_{ij2} \overline{\vee} \cdots \overline{\vee} r_{ijm} = \infty$

Logic multiplication ($\overline{\wedge}$) is used to aggregate relations on a relation path from c_i to c_j to find the relation from the head criterion to the tail criterion. It is defined as:

1) $-1 \overline{\wedge} -1 = -1$, $1 \overline{\wedge} 1 = -1$, $1 \overline{\wedge} -1 = 1$.
2) $\forall r_{lh}^0, l, h \in \{i, 1, ..., k, j\}, r_{lh}^0 \overline{\wedge} 0 = 0$.
3) $\overline{\wedge}$ satisfies left associativity,

   i.e. $x_{12}^0 \overline{\wedge} x_{23}^0 \overline{\wedge} x_{34}^0 = (x_{12}^0 \overline{\wedge} x_{23}^0) \overline{\wedge} x_{34}^0$.

For a set of relations $\{r_{ij}\}$, if one of the following two cases exists, then there is **inconsistency** in the relations: 1) $\exists r_{ij} = -r_{ji}$; 2) for m paths between c_i and c_j, $r_{ij1} \triangledown r_{ij2} \triangledown \cdots \triangledown r_{ijm} = \infty$. The corresponding relation matrix is called **inconsistent matrix**. A relation matrix (*RLM*) is a **consistent matrix** if the matrix does not have any of the above two properties. A **reachability matrix** (*RchM*) is a transitive relation matrix. It is **stable** (i.e., $RchM = RLM^k = RLM^{k+1}$) and **symmetric** (i.e. $\forall i, j, r_{ij} = r_{ji}$).

The meaning of the logic operations and how to use them are explained by the interactive relations among four criteria $\{c_1, c_2, c_3, c_4\}$, which is shown in Fig.1. The Fig.1 (a) is an initial relation matrix given by an expert, showing that:

1) $c_1[-1)c_4 \,\&\, c_4[-1)c_1 \Rightarrow c_1(-1)c_4$: c_1 and c_4 are directly conflicting with each other.
2) $c_1[-1)c_3$: c_1 directly opposes to c_3.
3) $c_1(-1)c_4(1)c_3 \Rightarrow c_1(-1 \barwedge 1)c_3 \Rightarrow c_1(1^1_{c_4})c_3$: c_1 and c_3 are transitively supporting each other via c_4.
4) inconsistencies:
   a. from 2) and 3), $c_1[-1 \cup 1^2_{c_4})c_3 \Rightarrow c_1[-1 \triangledown 1)c_3 \Rightarrow c_1[\infty)c_3$: the relation from c_1 to c_3 is confused due to the inconsistency between their direct relation and their transitive relation via c_4.
   b. $c_1[1^1_{c_3})c_2 \,\&\&\, c_2[-1^2_{c_3,c_4})c_1 \Rightarrow c_1(1 \triangledown -1)c_2 \Rightarrow c_1(\infty)c_2$: the relation between c_1 and c_2 are not symmetric.

An interaction process that can help the experts establish an inconsistent metric is illustrated in Fig.1 (a). The relation matrix of Fig.1 (a) is:

$$X = \begin{array}{c} \\ c_1 \\ c_2 \\ c_3 \\ c_4 \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & c_3 & c_4 \end{array} \\ \begin{pmatrix} -1 & 0 & -1 & -1 \\ 0 & -1 & 1 & 0 \\ 0 & 1 & -1 & 1 \\ -1 & 0 & 1 & -1 \end{pmatrix} \end{array}$$

The power of X is increased in order to identify the transitive relations, until the matrix reaches its stable state, i.e., the reachability matrix.

1) Check the direct inconsistent relations in *X*. If there are direct inconsistencies, return the position of the inconsistent relations. Experts revise the *RLM*. There is no inconsistency in *X*.
2) Or else, increase the power of the matrix, and record the additive vectors and the median matrix in each power-raised step, i.e. $X^k, k = \{2,3,...\}$, and $r^k_{ij}, i, j \in \{1,2,3,4\}$.

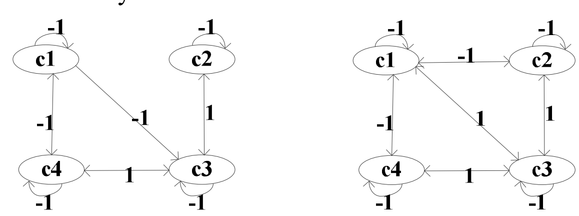
   If there are inconsistencies in the vectors or in the median matrix, the increasing process will be terminated, and the conflicting elements will be detected and be forwarded to experts. E.g., in X^2 , $c_3[1^1)c_1$ and $c_1[\infty^1)c_3$, but in $X, c_1[-1^0)c_3$. Therefore, the additive vectors for the two positions are returned to the experts. E.g., the additive vector for position (c3, c1) is calculated as:

$$c_3[1^1)c_1 \Leftarrow (0,0,-1,1) \odot (-1,0,0,-1)^T$$
$$\triangleq ((0 \barwedge -1) \triangledown (0 \barwedge 0) \triangledown (-1 \barwedge 0) \triangledown (1 \barwedge -1))$$
$$\triangleq (0 \triangledown 0 \triangledown 0 \triangledown 1)$$

   For position (c1, c3):

$$c_1[\infty^1)c_3 \Leftarrow (-1,0,-1,-1) \odot (-1,1,-1,1)^T$$
$$\triangleq ((-1 \barwedge -1) \triangledown (0 \barwedge 1) \triangledown (-1 \barwedge -1) \triangledown (-1 \barwedge 1))$$
$$\triangleq (-1 \triangledown 0 \triangledown -1 \triangledown 1)$$

3) The experts adjust the relation matrix based on the returned additive vectors and the powered matrix. E.g., the inconsistency between c_1 and c_3 can be seen from two aspects: 1) $c_1[\infty^1)c_3$; 2) the two additives vectors $(\overset{c_1}{0} \triangledown \overset{c_2}{0} \triangledown \overset{c_3}{0} \triangledown \overset{c_4}{1})$ and $(\overset{c_1}{-1} \triangledown \overset{c_2}{0} \triangledown \overset{c_3}{-1} \triangledown \overset{c_4}{1})$ clearly show that $c_3[1^1_{c_4})c_1$ and $c_1[1^1_{c_4})c_3$, (both inconsistent with $c_1[-1^0)c_3$). Thus, the relations among c_1, c_3, and c_4 should be reviewed by experts, and corresponding adjustment needs to be done. In Fig. 1, the relation is changed to $c_1[1^0)c_3$ based on the expert knowledge.
4) Restart the powering process until the stable matrix is achieved and there is no termination and feedback in the process, obtaining the reachability matrix (see Fig.1 (b)). We can see that the relations $c_3[1^0)c_1$ and $c_1(-1^0)c_2$ are transitively discovered from the initial relation matrix.



(a) (b)

Fig. 1. Interactive relations among criteria $\{c_1, c_2, c_3, c_4\}$: (a) inconsistent relations; (b) transitive relations.

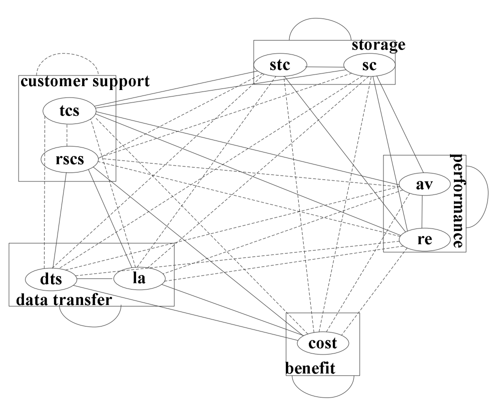


Fig. 2. IF-ANP network for Cloud storage service.

An IF-ANP network can be induced based on a consistent relation matrix (*CRLM*). For example, an IF-ANP corresponding to $CRLM_{cloud}$ is shown in Fig.2. Details of IF-ANP will be given in Section 4.

IV. Interactive Fuzzy ANP Determining a Fuzzy Measure

In this section, an improved ANP model is proposed based on the theory of criteria interdependence, namely interactive fuzzy ANP (IF-ANP). An IF-ANP model is an ANP network that is able to: 1) deal with cognitive and expressional uncertainties of decision makers, usually by using linguistic variables as inputs for pair-wise comparison matrixes; and 2) deduce the degree of interaction between criteria based on the pair-wise comparisons between direct relations, and the potential transitive relations. It models two types of criteria relations—supporting and conflicting, which is structured by the reachability matrix of I-ISM. For example, the IF-ANP network for Cloud service selection is shown in Fig.2. The supportive relations between criteria are represented by dotted lines, while the unbroken lines represent the conflicting relations. A line without arrows signifies that the relation is symmetric. The IF-ANP inference process is conducted as follows.

1) Conduct normal pair-wise comparisons of FANP, and form fuzzy pair-wise comparison matrixes for criteria. Fuzzy linguistic variables (Table I) are applied to capture the fuzzy cognitions of decision makers.
2) Defuzzify the fuzzy pair-wise comparison matrixes by using α-cut defuzzification technique, in accordance with confidence levels (α) and optimism degrees (μ) of decision makers (e.g., α=0.5 and μ=0.5 are used for the example of Cloud service selection).
3) Deduce the weighted super matrix from the defuzzfied pair-wise matrixes, and normalize it by dividing the sum of all the elements in the matrix. Let the weighted super matrix $WSM = [q_{ij}]$, then the normalization is conducted as: $NWSM = [q_{ij} / \sum_{i,j} q_{ij}] = [\overline{q}_{ij}]$.
4) Multiply the *NWSM* with the symmetric reachability matrix to obtain a signed *NWSM*, and average the values on the symmetric positions to obtain a symmetric interaction degree matrix.
   Let $SM = RchM * NWSM = [s_{ij} * \overline{q}_{ij}] = [s\overline{q}_{ij}]$ the signed $NWSM, i, j \in \{1,...,n\}$, then the interaction degree matrix is $InterM = [(s\overline{q}_{ij} + s\overline{q}_{ji})/2] = [a_{ij}]$.
5) Obtain the importance ratio of singletons by conducting pair-wise comparisons between criteria. A pair-wise comparison matrix for singletons is a positive reciprocal matrix, reflecting the importance ratio between a pair of criteria with respect to decision makers' preference. The comparison process is similar to the pair-wise comparison in an ANP process. Let $M^{\sin} = [d_i / d_j]^{preference}$ represent the pair-wise compared matrix, where d_i / d_j is the compared weight ratio from criterion i to criterion j with respect to the user's preference. Then the eigen-vector corresponding to the maximum eigen-value of $M^{\sin}$ is a stable state, which reflects the ranking of the importance weights of singletons, and is represented as $SinW = (w_i)^T, i \in \{1,2,...,n\}$. It is normalized as $NSinW = (w_i / \sum_i w_i)^T = (a_i)^T$. E.g., given the decision makers' preference of criteria, the independent weights of the nine criteria in the Cloud example is
   $$NSinW_{cloud} = \begin{array}{ccccccccc} av & re & sc & stc & dts & la & tcs & rscs & \cos t \end{array}$$
   $$(0.143, 0.119, 0.092, 0.135, 0.108, 0.108, 0.097, 0.078, 0.122)^T$$
6) Calculate the fuzzy measure μ of criteria, which measures the importance of singletons (μ_i) and the importance of a pair of interactive criteria (μ_{ij}). They are defined as: $\mu_i = \mu(i,i) = a_i + a_i + a_{ii}$, $\mu_{ij} = \mu(i,j) = a_i + a_j + a_{ij}$, $i, j \in \{1,...,n\}$.
7) Normalize the fuzzy measure by $\overline{\mu}_{ij} = \mu_{ij} / \max(\mu_{ij})$, and calculate the 2-order additive fuzzy integral using formula (1):

$$Ch_\mu(e_k) = \sum_{c_i \in T} \begin{array}{l} a(\{c_i\}) u_i(c_i(e_k)) + \\ \sum_{\{c_i, c_j\} \subset T} a(\{c_i, c_j\}) \min\{u_i(c_i(e_k)), u_j(c_j(e_k))\}, \end{array} \quad (1).$$

E.g., the normalized fuzzy measure of the Cloud example is $FMeasure_{cloud} =$

$$\begin{array}{c} \\ av \\ re \\ sc \\ stc \\ dts \\ la \\ tcs \\ rscs \\ \cos t \end{array} \begin{array}{c} \begin{array}{ccccccccc} av & re & sc & stc & dts & la & tcs & rscs & \cos t \end{array} \\ \left[\begin{array}{ccccccccc} 0.804 & \mathbf{0.739} & 0.672 & \mathbf{0.8} & 0.795 & 0.795 & 0.681 & \mathbf{0.712} & 0.825 \\ & \mathbf{0.661} & \underline{1} & \mathbf{0.73} & \mathbf{0.724} & \mathbf{0.724} & \mathbf{0.611} & \mathbf{0.642} & \mathbf{0.75} \\ & & 0.507 & \mathbf{0.629} & 0.638 & 0.638 & 0.536 & \mathbf{0.553} & 0.67 \\ & & & \mathbf{0.771} & \mathbf{0.773} & \mathbf{0.773} & \mathbf{0.666} & \mathbf{0.68} & \mathbf{0.795} \\ & & & & 0.596 & 0.602 & 0.656 & \mathbf{0.526} & 0.677 \\ & & & & & 0.596 & 0.656 & \mathbf{0.526} & 0.677 \\ & & & & & & 0.53 & \mathbf{0.579} & 0.686 \\ & & & & & & & \mathbf{0.413} & \mathbf{0.582} \\ & & & & & & & & 0.736 \end{array}\right] \end{array}$$

V. Interactive Fuzzy ANP Determining a Fuzzy Measure

We apply the non-monotonic Choquet integral to the example of Cloud service selection, based on the nine evaluation criteria. The importance of the interactivity of couples of criteria has been identified in Section 4.

A. User-oriented Sigmoid Utility Function

Choosing suitable Cloud services is a multicriteria decision making problem, requiring the evaluation and ranking of Cloud services based on their performance utilities. Service performance utility does not only rely on the marginal utilities of criteria, but also on the degree of satisfaction experienced by users in terms of the performance of the practical criteria. In Cloud service selection environment, service users (i.e., decision makers) typically utilize a lower bound or a scale with upper and lower limits to express their requirements on criteria performance. However, even if the performance value of a criterion from a service provider is higher than the required value (for monotonic criteria) or within the expected scale, we cannot say that the user is 100% satisfied with the value.Users may have different degrees of satisfaction with the performance of different criteria. On the other hand, a service should not be filtered out if the performance of a criterion is outside the bounds of the expected performance. Therefore, an elastic utility function is needed to measure users' satisfiability for different criteria and application contexts according to their specific requirements. This work introduces a sigmoid utility function by giving the rights of determining the value of function parameters to service requesters, according to their preference and specific requirements.

A sigmoid utility function is in the form of (2):

$$f(x)=\begin{cases}(1+e^{-a(x-b)})^{-1} & ,x=c,c\in C_B\\ 1-(1+e^{-a(x-b)})^{-1} & ,x=c,c\in C_C\end{cases} \qquad (2).$$

where c is a criterion, x is a performance value of the criterion c, C_B is a set of benefit criteria, and C_C is a set of cost criteria; the parameters a and b are the control parameters, where a decides the steepness of the function, i.e., it determines the rate of change of the function at a certain point; b controls the centre of the function, i.e., the position and the scale of the function along x-coordinate. Fig. 3 shows an example of the sigmoid function. We can see that it is monotonically increasing, scaling in the range [0,1]. And due to its gentle change rate with respect to a change of variables, it is capable of modeling criteria requirements effectively.

For each criterion, the parameters of the sigmoid function are defined based on user requirements and the original normalized decision matrix. Assume that there are m alternatives $\{a_1,...,a_m\}$, with n evaluation criteria $\{c_1,...,c_n\}$, then the performance matrix is: $PM=(x_{ij}),i\in\{1,...,m\},j\in\{1,...,n\}$. The parameters of the utility function are determined by the following:

Let ur_j be user-requested performance of benefit (*resp.*cost) criterion *j*. Firstly, the upper (*resp.*lower) limit of the sigmoid function is set as ur_j, which adapts to the assumption that the utility of a criterion will increase (*resp.*decrease) less sharply if the practical criterion performance is higher (*resp.*lower) than user requirements. The central point of the utility function is $b=ur_j-\varepsilon,\varepsilon=\min\{\varepsilon^{'},|ur_j-(x_j^-+x_j^*)/2|\}$ (*resp.* $b=ur_j+\varepsilon$), where $\varepsilon^{'}$ is a small value defined by experts and is identified according to the reality that if the practical performance of a criterion is below (*resp.* above) the user-requested performance, the utility of the criterion will decrease (*resp.* increase) dramatically. Parameter a helps to decide the steepness of the function, which is identified as $a=\arg\max_a\{(\partial f(x)/\partial x)\,|\,x=ur_j\}$ (*resp.* $a=\arg\min_a\{(\partial f(x)/\partial x)\,|\,x=ur_j\}$).

For example, for a benefit criterion *reliability*, assume that a user requirement is $ur_j=95\%$, $b=ur_j-\varepsilon=ur_j-0.05=0.9$, then $a=\arg\max_a\{\partial f(x)/\partial x\,|\,x=95,b=90\}=0.28$. The utility function is drawn as $f^1(x)$ in Fig.3. The function $f^2(x)$ is a linear function that demonstrates the change of the utility simply, without the consideration of the utility changing rate in different contexts, where, $x_j^-=\arg_x\lim\left(f^1(x)\right)=\sigma^-,\sigma^-\to 0$, $x_j^+=\arg_x\lim\left(f^1(x)\right)=\sigma^+,\sigma^+\to 1$, and $(x_j^++x_j^-)/2=b$.

The tangent line of the sigmoid function paralleling the linear function is at the point of $x=97\%$. It indicates that the utility of the availability will change slowly if the practical performance is higher than 97%, while if the practical performance is lower than 97%, the utility will change dramatically.

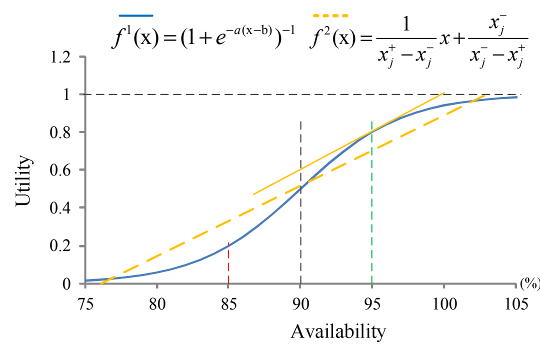


Fig. 3. Sigmoid utility function of *availability*.

B. *Data collection and parameter determination for utility functions*

Information of ten Cloud storage service providers (including JustCloud[1], DropBox[2], ZipCloud[3], etc.) is collected from SLAs or service descriptions provided by service providers, and from service monitoring and evaluation websites, e.g., TopTenReviews[4], RoyPingDom[5], BoxFreeIT[6], etc. The matrices for the nine criteria are defined in Table II, where (B) indicates a benefit criterion, and (C) indicates a cost criterion. Table III shows the collected criteria data. An example of user requirements on criteria performance is given in Table IV.

Combined with the fuzzy measure $FMeasure_{cloud}$, the Choquet integral utilities of the ten alternatives can be worked out, and are shown in the last column of Table V.

[1] http://www.justcloud.com/
[2] https://www.dropbox.com/
[3] http://www.zipcloud.com/
[4] http://www.toptenreviews.com/
[5] http://royal.pingdom.com/
[6] http://boxfreeit.com.au/

TABLE II. DEFINITIONS AND METRIC OF CRITERIA FOR CLOUD SERVICES

Criteria	Definition	Measurement Matrices
av (B)	a measure of the rate of time when the equipment is in an operable state	av = uptime/(uptime+downtime)
re (B)	a measure of the probability that an item will perform its intended function for a specified interval under stated conditions	decided by the actual availability (ac_av) and the availability defined in SLA (sla_av): if ac_av >= sla_av, re=1; else, re=1- (sla_av – ac_av) / sla_av
sc (B)	the ability of a service provider to scale resources in order to handle a large number of user requests simultaneously	check whether it is possible to upgrade without having to re-upload files (Boolean value {0,1})
stc (B)	storage volume	maximum storage volume that can be guaranteed by the service provider
la (C)	duration of transferring certain volume of data	time (s) of uploading a file (1MB). Ten time tests were done at different time points: 8am, 10am, 1pm, 4pm, 8pm, and 11pm on 22 and 25/06/2013, on the ten Cloud storage platforms. Average value is adopted
dts (C)	amount of data that is transmitted in a single unit of time (i.e., throughput)	maximum throughput (MB/s) achieved in the tests. Data from the tests above
tcs (B)	Consider 5 customer services: online chat support, email support, phone support, support forums, white papers	number of matched customer services between the provided and user requested*1 + number of the remaining customer services of the provided (i.e., nonmatched)*0.33
rscs (C)	response speed of customer service	record the time (mins) taken by the service provider to answer emails and online chat
cost (C)	price of the storage service	$/month/50GB

TABLE III. COLLECTED CRITERIA DATA OF 10 SERVICE PROVIDERS (NAMES ARE NOT GIVEN FOR KEEPING PRIVACY)

	sla_av (%)	ac_av (%)	re (%)	sc	stc (GB)	dts (mb/s)	la (s)	tcs	rscs (mins)	cost ($)
sp1	0.9999	0.9974	0.97	0	500	37.992	36.181	Email, Forums, White Papers	70	4.99
sp2	0.999	0.975	0.975	1	350	55.762	51.2	Chat, Email, Phone, White Papers	70	4.63
sp3	0.999	0.975	0.975	1	200	35.489	32.768	Email, Forums, White Papers	55	3.3
sp4	0.999	0.9	0.9	1	400	43.875	40.96	Chat, Email, White Papers	75	8.33
sp5	0.999	0.97	0.97	1	250	65.596	61.44	Email, Support Forums	75	2.99
sp6	0.999	0.9	0.9	1	500	83.33	81.92	Email, Forums, White Papers	150	3
sp7	0.999	0.9999	0.97	0	250	50.215	45.739	Email, Forums, White Papers	30	14.99
sp8	0.999	0.9999	0.93	1	183	64.068	61.44	Chat, Email, Phone, Forums	165	9.99
sp9	0.99	0.95	0.95	0	250	61.332	58.027	Chat, Email, Phone,White Papers	45	4.16
sp10	0.9	0.96	0.94	1	500	63.487	60.66	Email, Phone, Forums	120	2.08

TABLE IV. USER REQUIREMENTS ON CRITERIA PERFORMANCE

av	re	sc	stc	dts	la	tcs	rscs	cost
≥97%	≥95%	1	≥300G	≤50s	≤45s	Email, Phone, Forums	≤60mins	≤$10

TABLE V. MARGINAL UTILITIES AND FUZZY INTEGRAL UTILITIES OF CRITERIA

	av	re	sc	stc	dts	la	tcs	rscs	cost	Choquet integral
sp1	0.9749	0.9903	0	0.9999	0.9737	0.9487	0.8759	0.7549	0.9997	22.3836
sp2	0.8732	0.9955	1	0.9734	0.6357	0.6431	1.0000	0.7549	0.9998	24.5267
sp3	0.8732	0.9955	1	0.0832	0.9828	0.9691	0.8759	0.8581	1.0000	22.3342
sp4	0.0207	0.0021	1	0.9963	0.9310	0.8981	0.6241	0.7109	0.9358	14.5735
sp5	0.8240	0.9903	1	0.4013	0.2433	0.2693	0.7519	0.7109	1.0000	16.5107
sp6	0.0207	0.0021	1	0.9999	0.0150	0.0152	0.8759	0.0776	1.0000	6.7013
sp7	0.9792	0.9903	0	0.4013	0.8192	0.8078	0.8759	0.9491	0.0003	13.8811
sp8	0.9792	0.1760	1	0.0439	0.2949	0.2693	1.0000	0.0411	0.5000	8.5938
sp9	0.5000	**0.8240**	0	**0.4013**	0.4010	0.3848	1.0000	**0.9047**	0.9999	13.1972
sp10	0.6839	**0.5000**	0	**0.9999**	0.3161	0.2937	1.1278	**0.2451**	1.0000	12.018

TABLE VI. COMPARISON OF ALTERNATIVE RANKING BETWEEN FUZZY INTEGRAL (FI) AND SWA

	1 (Top)	2	3	4	5	6	7	8	9	10
Utility FI	24.526	22.383	22.334	16.511	14.573	13.881	13.197	12.02	8.594	6.701
Rank FI	sp2	sp1	sp3	sp5	sp4	sp7	**sp9**	**sp10**	sp8	sp6
Utility SWA	6.183	6.062	5.821	4.816	4.605	4.529	4.262	4.188	3.369	3.129
Rank SWA	sp2	sp1	sp3	sp5	sp4	sp7	**sp10**	**sp9**	sp8	sp6

C. Comparative analysis

The proposed 2-additive fuzzy integral approach is compared with the simple weighted additive (SWA) approach with the same pair-wise comparison inputs to IF-ANP, and marginal criteria utilities. The independent weights of criteria used by SWA is

$$\overline{NSinW_{cloud}} = (a_i / \max(a_i))^T$$

$$= (1, \mathbf{0.835}, 0.646, \mathbf{0.948}, 0.756, 0.756, 0.68, \mathbf{0.545}, 0.853)^T$$

The alternative ranking based on these two approaches is compared in Table VI. We can see that they produce similar ranking orders although their utilities are very different. The utilities from the fuzzy integral are much higher than the SWA-based utilities. The main reason is the fuzzy integral considers both utilities of singletons and criteria interactions. The difference in the ranking order is between sp9 and sp10. The fuzzy integral approach indicates that sp9 is preferred to sp10, in contrast to the result produced by the SWA approach. From Table V, the marginal utilities of criterion *re*, criterion *stc*, and criterion *rscs* are of large differences between sp9 and sp10 (highlighted with bold). The SWA approach linearly integrates the marginal utilities using the independent weights $\overline{NSinW_{cloud}}$, which shows that *stc* is more important than *rscs* (0.948 > 0.545), and the utilities of *stc* of sp10 (0.999) is larger than that of sp9 (0.401), which tends to put sp10 on a higher preference level than sp9. However, the fuzzy integral considers the interactive importance. The fuzzy measure $FMeasure_{cloud}$ shows that the criterion *re* is very important when it interacts with other criteria (especially with *sc*), helping to increase the ranking rate of sp9 (0.824 in Table V > 0.5 of sp10). The comparison result shows higher rationality of the proposed approach compared with SWA.

VI. Conclusion

This paper proposed a MCDM framework that models the interactive relations between evaluation criteria, and that is capable of handling the information fuzziness when facing a great amount of uncertain and inaccurate data. It combines the complementary techniques of ISM and ANP to form a stable decision-making structure, and to deduce the interactive importance between pairs of criteria. In the future, more simulations need to be conducted to prove the efficiency of the proposed framework, and techniques for dealing with big data will be further explored and applied to improve the present work, helping to discovery, classify and analyze the huge amounts information in order to support rational decisionmaking.

References

[1] A. Mosavi, "Data mining for decision making in engineering optimal design", *J. Artif. Intell. Res. & Data Min.*, vol. 1, 2013.

[2] F.K. Hussain, and O.K. Hussain. "Towards multicriteria cloud service selection", in *5th Int. Conf. Innovative Mobile and Internet Services in Ubiquitous Computing*, 2011, pp. 44-48.

[3] D. Bouyssou (ed.), Evaluation and decision models: a critical perspective, vol. 32, Springer, 2000.

[4] T.L. Saaty, "The analytic network process", Ir. J. Oper. Res., vol. 1, no. 1, 2008, pp. 1-27.

[5] B.Roy, "Problems and methods with multiple objective functions", Math. program, vol. 1, no. 1, 1971, pp. 239-266.

[6] S. Angilella, S. Greco, F. Lamantia, and B. Matarazzo, "Assessing nonadditive utility for multicriteria decision aid", Eur. J. Oper. Res., vol. 158, no. 3, 2004, pp. 734-744.

[7] R.M. Rodriguez, L. Martinez, and F. Herrera, "Hesitant fuzzy linguistic term sets for decision making", IEEE T. Fuzzy Syst., vol. 20, no. 1, 2012, pp. 109-119.

[8] G. Kannan, and A.N. Haq, "Analysis of interactions of criteria and subcriteria for the selection of supplier in the built-in-order supply chain environment", Int. J. Prod. Res., vol. 45, no. 17, 2007, pp. 3831-3852.

[9] J. Thakkar, S.G. Deshmukh, A.D. Gupta, and R. Shankar, "Development of a balanced scorecard: an integrated approach of interpretive structural modeling (ISM) and analytic network process (ANP) ", Int. J. Prod. Perform. Manag., vol. 56, no. 1, 2006, pp. 25-59.

[10] T.L. Saaty, "Decision making for leaders: the analytic hierarchy process for decisions in a complex world, new edition 2001 (analytic hierarchy process series, vol. 2) ", PA: RWS Publications, 1999.

[11] T.L. Saaty, "Decision making—the analytic hierarchy and network processes (AHP/ANP) ", J. Syst. Sci. Syst. Eng., 2004, vol. 13, no. 1, pp. 1-35.

[12] S. Sipahi, and M. Timor, "The analytic hierarchy process and analytic network process: an overview of applications", Manag. Decis., vol. 48, no. 5, 2010, pp. 775-808.

[13] T.L. Saaty, and L.G. Vargas, "How to Make a Decision", in Models, Methods, Concepts & Applications of the Analytic Hierarchy Process. 2012, Springer. pp. 1-21.

[14] W. Pedrycz, and M. Song, "Analytic hierarchy process (AHP) in group decision making and its optimization with an allocation of information granularit", IEEE T. Fuzzy Syst., vol. 19, no. 3, 2011, pp. 527-539.

[15] T. Demirel, N.Ç. Demirel, and C. Kahraman, "Multicriteria warehouse location selection using Choquet integral", Expert Syst.Appl., vol. 37, no. 5, 2010, pp. 3943-3952.

[16] M. Grabisch, "k-order additive discrete fuzzy measures and their representation", Fuzzy set. syst., vol. 92, no. 2, 1997, pp. 167-189.

[17] H.-H. Tsai, and I.-Y. Lu, "The evaluation of service quality using generalized Choquet integral", Inform. Sciences, vol. 176, no. 6, 2006. pp. 640-663.

[18] M. Grabisch, "Alternative representations of discrete fuzzy measures for decision making", Int. J. Uncertain. Fuzz., vol. 5, no. 5, 1997, pp. 587-607.

[19] T. Murofushi, M. Sugeno, and M. Machida, "Nonmonotonic fuzzy measures and the Choquet integral", Fuzzy set. Syst., vol. 64, no. 1, 1994, pp. 73-86.

[20] M.-F. Chen, and G.-H. Tzeng, "Combining grey relation and TOPSIS concepts for selecting an expatriate host country", Math. Comput. Model., vol. 40, no. 13, 2004, pp. 1473-1490.

[21] Z. Ayağ, and R. Gürcan Özdemir, "Evaluating machine tool alternatives through modified TOPSIS and alpha-cut based fuzzy ANP", Int. J. Prod. Econ., vol. 140, no. 2, 2012, pp. 630-636.

[22] C. Carlsson, and R. Fullér, "Multiple criteria decision making: the case for interdependence", Comput. Oper. Res., vol. 22, no. 3, 1995, pp. 251-260.

[23] M. Yurdakul, and Y.T. Ic, "Application of correlation test to criteria selection for multicriteria decision making (MCDM) models", Int. J. Adv. Manuf. Technol., vol. 40, no. 3, 2009. pp. 403-412.