Normal Cloud Model-Based Algorithm for Multi-Attribute Trusted Cloud Service Selection

YULI YANG[1], RUI LIU[1], YONGLE CHEN[1], TONG LI [ID][2], AND YI TANG [ID][3]

[1]College of Information and Computer, Taiyuan University of Technology, Taiyuan 030024, China
[2]School of Computer Science, Guangzhou University, Guangzhou 510006, China
[3]School of Mathematics and Information Science, Guangzhou University, Guangzhou 510006, China

Corresponding author: Tong Li (litongziyi@mail.nankai.edu.cn)

ABSTRACT With the wide deployment of cloud computing, many security challenges have arisen, such as data and storage integrity and virtualization security. The crisis of trust caused by these security issues has become one of the important factors restricting the wide applications of cloud service. Especially for security-sensitive users, it is challenging to quickly select a cloud service which has the high level of trust and can meet both the user preferences and specific functional demands. This paper explores the multi-granularity selection standard of trust level, the users' preference calculation model, and the cloud service selection algorithm. First, the trust evaluation mechanisms among different entities in the human society are fitted, and the multi-granularity selection standard of trust levels based on Gaussian cloud transformation is constructed. Then, the calculation model of user preferences based on the cloud analytic hierarchy process is developed. Finally, the trusted cloud service selection algorithm based on two-step fuzzy comprehensive evaluation is proposed and experimentally validated.

INDEX TERMS Cloud computing, cloud service selection, QoS, normal cloud model, trust mechanism.

I. INTRODUCTION

Due to the rapid development of cloud computing, Amazon, Google, Microsoft, and other providers of cloud services have launched a wide variety of cloud services, which allows users to handle large datasets stored in multiple distributed nodes in the similar way to handle local data. However, more and more security-sensitive users worry about security issues in cloud computing [1]. Many approaches have been proposed to enhance the users' right to control the data. For example, in order to preserve the confidentiality and security of data, a novel privacy-preserving Naive Bayes learning scheme with multiple data sources was proposed [2] and a novel cluster-based secure data aggregation scheme was designed [3]. The privacy-aware applications over big data in a hybrid cloud were proposed [4] and a flexible electronic health record sharing scheme was presented [5]. Li *et al.* [6] proposed a new attribute-based data sharing scheme to solve the data confidentiality problem in cloud data sharing, presented a hybrid cloud approach for secure authorized deduplication [7], and designed the significant permission identification method for machine learning [8]. An ensemble random forest algorithm was presented for big data analysis [9]. Huang *et al.* [10] formalized the security notion of non-malleability to solve data

security and privacy protection problems. In addition, in order to improve the security of the cloud computing environment, a lot of security challenges have been researched. A novel traceable group data sharing scheme was proposed to support anonymous multiple users in public clouds [11]. An additively homomorphic encryption scheme was employed [12]. A new ID-based linear homomorphic signature scheme was presented [13]. A dynamic fully homomorphic encryption-based Merkle tree was constructed in [14].

Unfortunately, the trust crisis caused by security problems of cloud services is still one of the important factors of restricting the wide applications of cloud services. Many researchers tried to introduce the trust mechanism into the cloud service selection process and achieved remarkable results [15]. However, there are many problems to be solved. Users have different trust demands. Generally speaking, security-sensitive users have the higher granularity division demands for the level of trust, and vice versa. Therefore, users' different trust demands should be fully considered in cloud service selection. In addition, the cloud service selection is a typical multi-attribute decision-making problem [16] and the following problems remain to be solved.

A. QUANTIFICATION OF CLOUD SERVICE ATTRIBUTES

Due to the dynamics and uncertainty of the cloud computing environment, the QoS (Quality of Service) of cloud services claimed by service providers generally fluctuates within a certain range. Moreover, the experienced QoS is different among users due to the differences in users' device type, network location and context [17]. So, the way to describe the uncertainty of QoS as accurately as possible has become a key issue in the selection process of trusted cloud services.

B. WEIGHT COEFFICIENTS OF USERS' PREFERENCES

In view of vagueness, inaccuracy and incompleteness of user preferences [18], the accurate characterization of users' preferences for different attributes of cloud services is important for users to select the trusted cloud service. Therefore, it is necessary to construct an accurate computational model for describing users' preferences.

C. RANKING CLOUD SERVICES

Considering that more and more cloud services will be available in the cloud market, it will be more complicated to select the optimal cloud services [19]. Therefore, it is necessary to develop an effective strategy to rank the increasing cloud services for the selection of trusted cloud services.

To solve the above problems, the multi-attribute trusted cloud service selection strategy is designed. It fits the trust evaluation and measurement mechanism in human society. Based on the mechanism, a simple and efficient cloud service selection strategy is designed to help users to select trusted cloud services. The main contributions of this paper are outlined as follows. Firstly, multi-granularity selection standard of trust level is designed. Then, the computational model of users' preferences based on the cloud analytic hierarchy process is designed to describe users' preferences for different attributes of cloud services. Finally, the novel algorithm of trusted cloud service selection is proposed to provide the simple and effective decision-making basis for users.

The remainder of this paper is organized as follows. Related studies on cloud service selection and the normal cloud model are reviewed in Section II. The multi-attribute trusted cloud service selection algorithm is presented in Section III. The feasibility of the proposed algorithm is explored by simulation experiments in Section IV and conclusions and suggestions for future research are presented in Section V.

II. RELATED STUDIES

In order to better understand the idea of this paper, firstly, the current research status of trusted cloud service selection is given in Subsection A. Then, the normal cloud model is introduced in Subsection B.

A. TRUSTED CLOUD SERVICE SELECTION

The essence of the trusted cloud service selection is to select the trusted cloud service from the cloud services with the same function but different quality. To facilitate cloud service users to select trusted services, many approaches have been proposed for cloud service ranking and selection in recent years. The proposed methods are based on two theories: the multi-criteria decision theory and the combinatorial optimization theory.

1) MCDM-BASED APPROACHES FOR CLOUD SERVICE SELECTION

To evaluate and rank multi-attribute cloud services, Lee S and Seo K. designed a hybrid MCDM model, which adopted balanced scorecard, fuzzy Delphi method and fuzzy analytical hierarchy process, for enterprise users to select the best cloud service [20]. To select the cloud service that satisfied the users' demands, a novel fuzzy user-oriented cloud service selection system was designed by Sun L with fuzzy Cloud ontology, fuzzy AHP approach, and fuzzy TOPSIS approach [21]. To simplify the multimedia service selection process and obtain the more accurate selection result, Qi *et al.* [22] proposed a multimedia service selection method based on Weighted Principal Component Analysis. Taking into account users' preferences and expectations, Ding *et al.* [23] designed a cloud service ranking and prediction algorithm to help users to select the most satisfied cloud service. Considering the cost and risk of cloud service in different periods, Ma *et al.* [17] proposed a time-aware trusted cloud service selection algorithm and designed a ranking cloud service algorithm with interval neutrosophic set. In view of the risks in the process of cloud service selection, Lin *et al.* [24] designed a risk assessment algorithm based on the cloud model theory to improve the speed and success rate of cloud service selection. Sidhu *et al.* proposed the trusted cloud service selection strategy based on MCDM. This strategy was mainly supported by Analytic Hierarchy Process, Technique for Order of Preference by Similarity to Ideal Solution and Preference Ranking Organization Method [25]. Yang *et al.* [26] designed a multi-QoS-aware cloud service selection strategy and adopted the analytic hierarchy process method to select the appropriate cloud service.

2) OPTIMIZATION-BASED APPROACHES FOR CLOUD SERVICE SELECTION

The problem of cloud service selection based on combinatorial optimization theory is mainly solved by dynamic programming, linear programming and meta-heuristic algorithms and so on. Considering QoS indexes and the relationship among QoS key factors of different kinds of cloud services, Huang *et al.* [27] designed a new chaos control optimal algorithm to solve the problem of cloud service composition optimal-selection. To maximize the users' profits, Jrad *et al.* [28] developed a utility–based, dynamic and flexible matching algorithm to help customers to make clever decisions. To meet the demands of complicated tasks, Zhou and Yao [29] presented a hybrid artificial bee colony algorithm to select the optimal cloud manufacturing service composition. Esposito *et al.* [30] employed the fuzzy set

theory to describe the vagueness in the subjective preferences of customers, and designed the cloud service selection strategy with fuzzy logics, theory of evidence, and game theory. To better multiplex and share physical hosts in the cloud data centers, a VM placement algorithm based on the peak workload characteristics was designed [31]. Lin *et al.* [32] extended CloudSim with a multi-resource scheduling and power consumption model to improve the evaluation precision of power consumption in dynamic multi-resource scheduling. A scheduling algorithm based on heterogeneous multicore processors was proposed to reduce memory latency and enhance parallelism [33]. A hybrid energy-aware resource allocation approach was designed to help users to acquire energy-efficient and satisfied manufacturing services [34]. Considering the accuracy and diversity, Ding *et al.* [35] designed two modified ranking prediction and recommendation algorithms to help customers to make prompt decisions.

In previous studies, the methods of trusted cloud service selection had some limitations. For example, existing methods for determining the trust level of cloud service cannot meet users' the demand of the multi-granularity trust. In addition, the fuzziness and randomness of different attribute weight coefficients were not considered. Aiming at these problems, firstly, the partitioning algorithm of multiple-granularity trust level is put forward to meet users' the demand of multiple-granularity trust. Then, CAHP is designed to describe weight coefficients of different attributes. Finally, different cloud services are evaluated and sorted by computing similarity of the normal cloud model, thus providing a simple and effective decision-making method for users.

B. NORMAL CLOUD MODEL

To express many uncertainness concepts in natural and social sciences effectively, based normal distribution and Gaussian membership function, Li *et al.* [36] proposed the normal cloud model, which described the randomness and fuzziness of uncertain concepts simultaneously and implemented the uncertain transformation between qualitative concepts and quantitative values with the forward normal cloud generator and backward normal cloud generator. Its definitions are given below.

Definition 1(Normal Cloud Model): Let *A* be a qualitative concept defined over a universe of discourse $U = \{u\}$. If $x \in U$ is a random instantiation of concept *A*, which satisfies $x \sim N(Ex, En'^2)$, $En' \sim N(En, He^2)$, and the certainty degree of *x* belonging to concept *A* satisfies $\mu = e^{\frac{-(x-Ex)^2}{2(En)^2}}$, then the distribution of *x* in the universe *U* is called a normal cloud and *x* is called a cloud drop.

The normal cloud model describes fuzziness and randomness of qualitative concepts with three numerical characteristics, namely, Expectation *Ex*, Entropy *En* and Hyper entropy *He*. *Ex* is the mathematical expectation of the cloud drops belonging to a concept in the universe. It is deemed as the

most representative sample of the qualitative concept. *En* is used to describe uncertainty degree of a qualitative concept, which can reflect the steepness of the normal cloud. The greater the value of *En* is, the wider the level range covered by the concept is. *He* is used to measure the uncertainty of *En*. The larger *He* is, the larger the dispersion of the cloud drop is. With forward normal cloud generator, the normal cloud (25, 3, 0.5) used to describe the uncertain concept "young" is generated in Figure 1. As can be seen from Fig. 1, most of cloud drops contributing to the concept of "young" are mainly concentrated in the interval [16], [33] due to "3En rules".
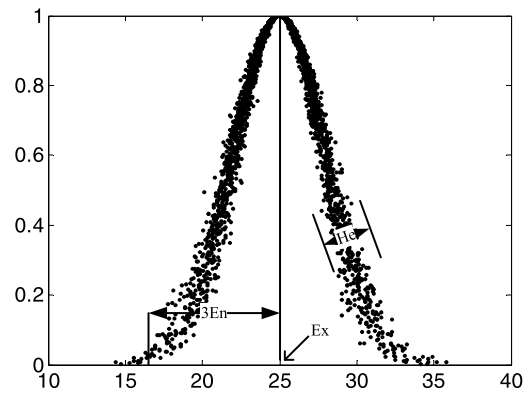

FIGURE 1. Three numerical characteristics of the cloud model.

III. ALGORITHM OF MULTI-ATTRIBUTE TRUSTED CLOUD SERVICE SELECTION

In order to help users to select suitable cloud services according to their preferences to different QoS, the trusted cloud service selection framework is designed in Subsection A and multi-granularity standard trust cloud used to describe the users' trust demands is given in Subsection B. The model of quantify cloud service attribute is designed in Subsection C. The method for calculating weight coefficient of user preferences is shown in Subsection D. The algorithm of multi-attribute trusted cloud service selection is presented in Subsection E.

A. A MEASUREMENT FRAMEWORK FOR TRUSTED CLOUD SERVICE SELECTION

In order to describe users' preferences to different attributes precisely, and provide effective decision-making, the measurement framework for trusted cloud service selection is designed based on the Service Measurement Index (SMI) framework designed by Cloud Services Measurement Initiative Consortium (CSMIC). As shown in Figure 2, in the left part, different attributes of the cloud service are normalized and the corresponding attribute cloud matrix based on the cloud model theory is generated. Then, in the right part, the cloud analytic hierarchy process is designed to describe users' preferences to different attributes of cloud services and generate the user-preferences cloud matrix. A synthetic trust
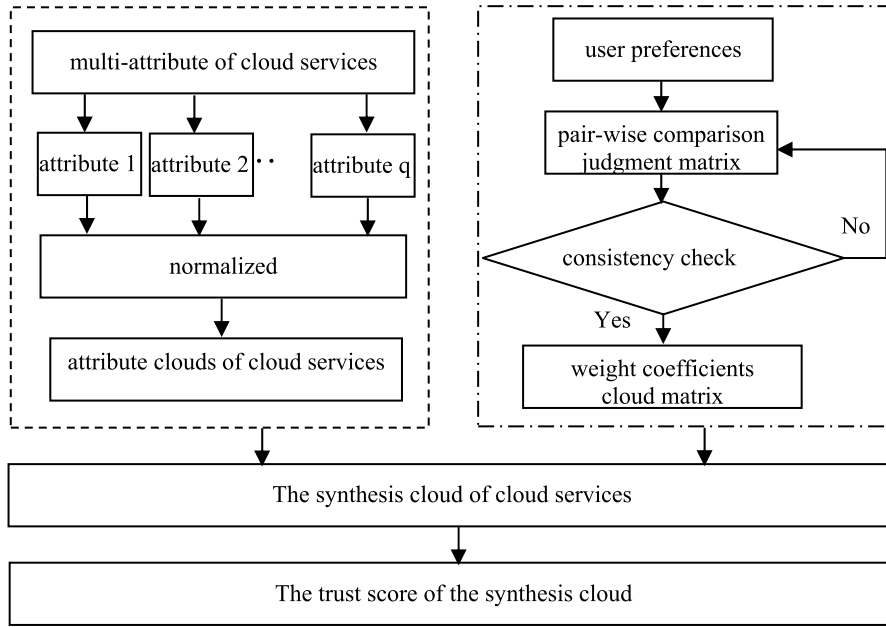
FIGURE 2. Three numerical characteristics of the cloud model.

cloud is generated by synthesizing the attribute cloud matrix and the user preference cloud matrix through synthesis operators. Finally, the trust value of the cloud service is obtained by calculating the similarity between the synthesized trust cloud and the standard trust cloud. The details of the implementation process are given below.

B. MULTI-GRANULARITY STANDARD TRUST CLOUD

According to the basis of the central limit theorem, the distribution of the user experience data is an approximate normal distribution, so the normal cloud model is used to describe the user experience data. Meanwhile, inspired by the conclusion that a sum of Gaussian distributions can be extracted from an original data set following normal distributions [37], a method is proposed to compute multi-granular trust level. The method aims to extract multiple normal could from the user experience data approximately following normal distributions as multi-granularity selection standard of trust level. The details are provided in Algorithm 1.

In Algorithm 1, first of all, the user experience data following normal distributions approximately are sorted in ascending order and grouped according to the number of trust levels M (Line 1-2). Then, $M - 2$ normal cloud model is generated with the backward normal cloud generator [36] (Line 3-8). Finally, $C(Ex_0, En_0, He_0)$ and $C(Ex_{M-1}, En_{M-1}, He_{M-1})$ are respectively generated according to $C(Ex_1, En_1, He_1)$ and $C(Ex_{M-2}, En_{M-2}, He_{M-2})$. Among them, Ex_0 and Ex_{M-1} are set to zero and one, which respectively represent "absolute untrust" and "absolute trust". According to "3En" rules, En_0 and En_{M-1} are equal to $\frac{1}{3}Ex_1$ and $\frac{1}{3}Ex_{M-1}$, respectively. Hyper entropy He_0 is set as $\frac{1}{3}En_0$ (Line 9-10).

C. QUANTIFICATION MODEL OF CLOUD SERVICE ATTRIBUTES

Supposing that there are Y cloud services provided the same service and that each cloud service includes q kinds of attributes. According to the different methods for describing attributes of cloud service contained in cloud Service Metrics Index (SMI) [38], the attributes are classified into three types: the attributes described with exact value, interval values and language values, and respectively denoted as q_1, q_2 and $q_3(q_1 + q_2 + q_3 = q)$. To describe the characteristics of fuzziness and randomness of the cloud service attributes, the normal cloud model, which can describe randomness and fuzziness, is used to quantify the three different types of cloud service attributes above. The details are provided below:

1) ATTRIBUTES DESCRIBED WITH EXACT VALUES

The value of ith cloud service's jth attribute is denotes as $x_{ij}(1 \leq i \leq Y, 1 \leq j \leq q_1)$. The values of negative attributes (e.g. cost and time) should be minimized, and the values of positive attributes (e.g. trust and availability) should be maximized. The normalized values of negative and positive attributes are respectively computed according to Eqs. (1) and (2), where Q_N^{max} (Q_N^{min}) is the maximal (minimal) value of negative attributes and Q_P^{max} (Q_P^{min}) is the maximal (minimal) value of positive attributes. The value of a normalized attribute is set to $x'_{ij}(0 \leq x'_{ij} \leq 1)$. The data sets following the normal distribution $normrnd(x'_{ij}, \delta)$ are generated firstly, and then the attribute clouds of different attributes denoted as

$$R_{i1} = \begin{bmatrix} Ex_{i1} & En_{i1} & He_{i1} \\ Ex_{i2} & En_{i2} & He_{i2} \\ \vdots & \vdots & \vdots \\ Ex_{iq_1} & En_{iq_1} & He_{iq_1} \end{bmatrix}$$

Algorithm 1 The Algorithm of Multi-Granular Standard Trust Cloud

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Input: Data samples following Gaussian distributions $X\{x_i|i = 1, 2, \cdots N\}$, the number of trust level $M \geq 3$

Output: M gaussian cloud model $C(Ex_k, En_k, He_k)$, $k = 1, 2, \cdots M$

1. Sort N data samples according to ascending order, and denoted as $X'\{x'_i|i = 1, 2, \cdots N\}\circ$
2. Divide N data samples into $M - 2$ groups, m is set equal to $M - 2$, each group contains r samples, and denoted as
$$X' = \begin{bmatrix} x'_{11}, x'_{12}, \cdots, x'_{1r} \\ x'_{21}, x'_{22}, \cdots, x'_{2r} \\ x'_{m1}, x'_{m2}, \cdots, x'_{mr} \end{bmatrix}$$
3.   *for i = 1 to m do*
4.   *for j = 1 to r do*
5. Compute the average value $\bar{X}'_i = \frac{1}{r} \sum_{k=1}^{r} x'_{ij}$ of all data sample point X'_i, its first-order absolute center distanc $Fcm_i = \frac{1}{r} \sum_{k=1}^{r} \left|x'_{ij} - \bar{X}'_i\right|$, and its the variance $Var_i = \frac{1}{r-1} \sum_{k=1}^{r} \left(x'_{ij} - \bar{X}'\right)^2$
6. Compute expectation $Ex_i = \bar{X}'$, entropy $En_i = \sqrt{\frac{\pi}{2}} \times Fcm_i$, and hyper entropy $He_i = \sqrt{Var_i - En_i^2}$
7.   *end for*
8.   *end for*
9.   Compute $C(Ex_0, En_0, He_0)$ according to $C(Ex_1, En_1, He_1)$, in which Ex_0 is set to zero, En_0 equals $\frac{1}{3}Ex_1$, and He_0 is $\frac{1}{3}En_0$
10. Compute $C(Ex_{M-1}, En_{M-1}, He_{M-1})$ according to $C(Ex_{M-2}, En_{M-2}, He_{M-2})$, in which Ex_{M-1} is set to 1, En_{M-1} equals $\frac{1}{3}Ex_{M-2}$, and He_{M-1} is $\frac{1}{3}En_{M-1}$

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are generated with the backward normal cloud generator [29].

$$U(N) = \frac{Q_N^{max} - Q_N}{Q_N^{max} - Q_N^{min}} \qquad (1)$$

$$U(P) = \frac{Q_P - Q_P^{min}}{Q_P^{max} - Q_P^{min}} \qquad (2)$$

2) ATTRIBUTES DESCRIBED WITH INTERVAL VALUES
Similar to the attributes described with exact values, the attributes described with interval values should be normalized according to Eqs. (1) and (2) firstly. Then, the attribute clouds

$$R_{i2} = \begin{bmatrix} Ex_{i1} & En_{i1} & He_{i1} \\ Ex_{i2} & En_{i2} & He_{i2} \\ \vdots & \vdots & \vdots \\ Ex_{iq_2} & En_{iq_2} & He_{iq_2} \end{bmatrix}$$

are generated according to $Ex_i = \frac{R_i^{min} + R_i^{max}}{2}$, $En_i = \frac{R_i^{max} - R_i^{min}}{3}$ and $He_i = \eta$ (η is constant), in which R_i^{min} and R_i^{max} denote

the lower and upper limits of the corresponding interval, respectively.

3) ATTRIBUTES DESCRIBED WITH LANGUAGE VALUES
The attributes described with the language value are transformed into attribute clouds and denoted as

$$R_{i3} = \begin{bmatrix} Ex_{i1} & En_{i1} & He_{i1} \\ Ex_{i2} & En_{i2} & He_{i2} \\ \vdots & \vdots & \vdots \\ Ex_{iq_3} & En_{iq_3} & He_{iq_3} \end{bmatrix}$$

according to multi-granular standard trust cloud, which is given in Section III.

D. WEIGHT COEFFICIENTS OF USERS' PREFERENCES
In view of the vagueness, inaccuracy and incompleteness of users' preferences, the cloud hierarchical analysis based on the AHP and normal cloud model is designed to compute the weight coefficient cloud matrix of different attributes. The steps are provided below.

Step 1: Assuming that q attributes are used to evaluate the trust level of cloud services. Instead of AHP in the 9th scale, intervals are used to describe the weights of different attributes [39] and build the pair-wise comparative judgment matrix A shown below.

In matrix A, the value of interval a_{ij} ranges from 0 to 9, and should satisfy the following properties: $a_{ji}^L = 1/a_{ij}^L$ and $a_{ji}^U = 1/a_{ij}^U$; $a_{ij} = [1, 1]$, where $i = j$.

Step 2: The weight coefficients of cloud services' different attributes are computed for consistency check.

Step 2.1: According to pair-wise comparison judgment matrix A, the numerical characteristic value of corresponding interval is computed according to the method shown in Section III and the result is denoted as the pair-wise comparison judgment cloud matrix A', as shown at the bottom of the next page.

Step 2.2: The consistency of A' is checked using Eq. (3) [40]. A' is considered to meet the condition of consistency check when Consistency Ratio (*C.I.*) is less than 0.1. Otherwise, the matrix should be modified appropriately by repeating the above steps.

$$C.I. = \frac{1}{q(q-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{q} \frac{He_{ij}}{Ex_{ij}} \qquad (3)$$

Step 2.3: According to pair-wise comparison judgment matrix A', the weight coefficient cloud matrix of different attributes

$$\bar{A}' = \begin{bmatrix} Ex_{a_1} & En_{a_1} & He_{a_1} \\ Ex_{a_2} & En_{a_2} & He_{a_2} \\ \vdots & \vdots & \vdots \\ Ex_{a_q} & En_{a_q} & He_{a_q} \end{bmatrix}^T$$

TABLE 1. Attribute clouds of cloud database servers from first to third.

Parameters	CDS_1	CDS_2	CDS_3
SP_{int}	(0.1152 ,0.0328 ,0.0100)	(0.0865 ,0.0156 ,0.0100)	(0.0876 ,0.0116 ,0.0100)
SP_{fp}	(0.1261 ,0.0229 ,0.0100)	(0.1068 ,0.0273 ,0.0100)	(0.0965 ,0.0174 ,0.0100)
MP_{sc}	(0.2859 ,0.0166 ,0.0100)	(0.2018 ,0.0277 ,0.0100)	(0.2984 ,0.0180 ,0.0100)
MP_{td}	(0.2777 ,0.0290 ,0.0100)	(0.2109 ,0.0168 ,0.0100)	(0.2825 ,0.0187 ,0.0100)
SRW_{dp}	(0.1395 ,0.0122 ,0.0100)	(0.0670 ,0.0166 ,0.0100)	(0.0137 ,0.0147 ,0.0100)
RRW_{dp}	(0.0942 ,0.0182 ,0.0100)	(0.0880 ,0.0139 ,0.0100)	(0.0138 ,0.0223 ,0.0100)
SRW_{pct}	(0.2170 ,0.0252 ,0.0100)	(0.1415 ,0.0250 ,0.0100)	(0.2493 ,0.0201 ,0.0100)
RRW_{pc}	(0.2045 ,0.0158 ,0.0100)	(0.1435 ,0.0210 ,0.0100)	(0.2219 ,0.0165 ,0.010)
N_l	(0.0892 ,0.0167 ,0.0100)	(0.2499 ,0.0193 ,0.0100)	(0.3653 ,0.0186 ,0.0100)
C_{od}	(0.0311 ,0.0238 ,0.0100)	(0.0256 ,0.0121 ,0.0100)	(0.0348 ,0.0317 ,0.0100)

is computed, in which the three numerical characteristics of the *i*th attribute cloud are computed according to the previous method [26].

E. METHOD FOR RANKING CLOUD SERVICES

In order to provide users with a simple and effective decision-making result, based on the evaluation index system of SIM, a novel improved two-level fuzzy comprehensive evaluation method is designed for ranking different cloud services. The details are provided below.

Firstly, The N attribute sets in the criteria layer are denoted as a set $X = \{X_1, X_2, \cdots X_N\}$ where $X = X_1 \cup X_2 \cup \cdots X_N$ and $X_i \cap X_j = \emptyset$ $(i \neq j)$. Similarly, $X_i = \{x_{i_1}, x_{i_2}, \cdots x_{i_{k_i}}\}$ is denoted as k_i attribute contained in X_i.

Secondly, for $X_i = \{x_1^{(i)}, x_2^{(i)}, \cdots x_{k_i}^{(i)}\}(1 \leq i \leq N)$, D_i is used to describe user preferences to sub-attribute $x_j^{(i)}$ $(1 \leq j \leq k_i)$, and R_i is the attribute cloud of X_i. According to the fuzzy synthesis operator based on cloud model, The first-level fuzzy comprehensive evaluation for X_i can be computed by Eq. (4).

$$B_i = D_i \circ R_i \qquad (4)$$

Thirdly, for attribute sets $X = \{X_1, X_2, \cdots X_N\}$, $T_j = \left[Ex_{a_j} \ En_{a_j} \ He_{a_j}\right]^T$ $(1 \leq j \leq q)$ is used to describe user preferences to attribute $X_i(1 \leq i \leq N)$ in X, and with the aid of the matrix B_i generated in the first-level fuzzy comprehensive evaluation, the second-level fuzzy comprehensive evaluation can be calculated as below:

$$C_i = T_j \circ B_j = C(Ex_{syn}, En_{syn}, He_{syn}) \qquad (5)$$

Fourthly, the trust score of the synthetic cloud is computed. According to the users' trust demands, the corresponding granularity standard trust cloud is selected. Then the similarity between the synthetic cloud and each standard trust cloud

is computed by Eq. (6), in which $\overrightarrow{V}_{C_1} = (Ex_1, En_1, He_1)$ and $\overrightarrow{V}_{C_2} = (Ex_2, En_2, He_2)$ are denoted as the attribute cloud vectors.

$$sim(\overrightarrow{V}_{C_1}, \overrightarrow{V}_{C2}) = cos(\overrightarrow{V}_{C_1}, \overrightarrow{V}_{C2}) = \frac{\overrightarrow{V}_{C_1} \cdot \overrightarrow{V}_{C2}}{\left\|\overrightarrow{V}_{C_1}\right\| \left\|\overrightarrow{V}_{C2}\right\|} \qquad (6)$$

Finally, the trust score of the synthesis cloud is computed by Eq. (7).

$$Score = SL + S_{max} \qquad (7)$$

In Eq. (7), S_{max} represents the maximum similarity value between the synthetic cloud and standard trust clouds and SL denotes the trust level of the corresponding standard trust clouds with the maximum similarity.

IV. SIMULATION EXPERIMENTS

CloudSim [41] is used to simulate the trusted cloud service selection process. Some experiments are designed to demonstrate the feasibility of the proposed algorithms.

A. MULTI-GRANULARITY TRUST LEVEL

To describe the user experience data following normal distributions, data sets following the normal distribution $normrnd(0.5, 0.167)$ are generated firstly. Then, according to the trust demands of users, Algorithm 1 is used to generate multi-granularity standard trust cloud.

According to Algorithm 1, the generated standard trust clouds with different granularity values (from 3 to 6) are given as follows. The standard trust cloud with granularity value of 3 is given in Fig. 3(a) and denoted as T[3] = {absolute distrust, neutral trust, absolute trust}. Standard trust cloud with the granularity value of 4 is given in Fig 3(b) and denoted

$$A' = \begin{bmatrix} a_{11}(Ex_{11}, En_{11}, He_{11}), & a_{12}(Ex_{12}, En_{12}, He_{12}), & \cdots, & a_{1q}(Ex_{1q}, En_{1q}, He_{1q}) \\ a_{21}(Ex_{21}, En_{21}, He_{21}), & a_{22}(Ex_{22}, En_{22}, He_{22}), & \cdots, & a_{2q}(Ex_{2q}, En_{2q}, He_{2q}) \\ \vdots & \vdots & \vdots & \vdots \\ a_{q1}(Ex_{q1}, En_{q1}, He_{q1}), & a_{q2}(Ex_{q2}, En_{q2}, He_{q2}), & \cdots, & a_{qq}(Ex_{qq}, En_{qq}, He_{qq}) \end{bmatrix}$$
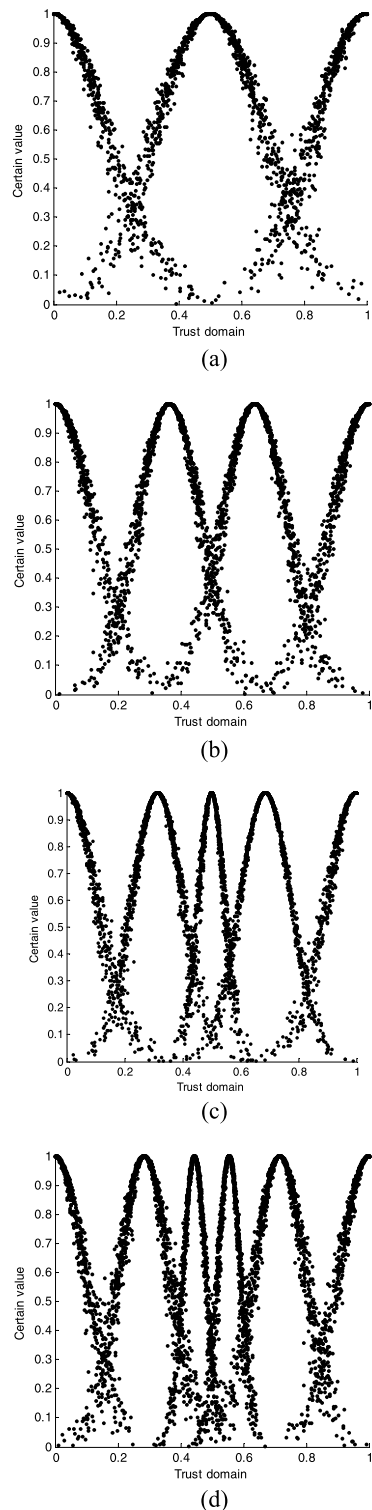
(a)

(b)

(c)

(d)

FIGURE 3. Multi-granular trust level.

as T[4] = {absolute distrust, low trust, high trust, absolute trust}. Standard trust cloud with the granularity value of 5 is given in Fig. 3(c) and denoted as T[5] = {absolute distrust, low trust, neutral trust, high trust, absolute trust}. Standard trust cloud with the granularity value of 6 is given in Fig. 3(d) and denoted as T[6] = {absolute distrust, extremely low

TABLE 2. The weight coefficient of user preferences.

Parameters	weight coefficients
SP_{int}	(1.0000,1.0000,1.0000)
SP_{fp}	(0.4699,0.4735,0.4729)
MP_{sc}	(0.2610,0.2687,0.2678)
MP_{td}	(0.2336,0.2358,0.2355)
SRW_{dp}	(0.1427,0.1484,0.1479)
RRW_{dp}	(0.1464 ,0.1488,0.1486)
SRW_{pct}	(0.1086,0.1122,0.1118)
RRW_{pc}	(0.1154,0.1167,0.1166)
N_l	(0.1188 ,0.1182,0.1182)
C_{od}	(0.1192,0.1171,0.1173)

trust, low trust, high trust, extremely high trust, absolute trust}. Compared with the traditional way to determine the level of trust based on subjective experiences, it utilizes the statistical theory to reduce subjective factors and describes the ambiguity and randomness of trust levels simultaneously. Moreover, it can accurately describe the users' trust demands with different granularity values and improve user satisfaction.

B. CASE STUDY

A sample dataset extracted by Sidhu J and Singh S from the Cloud Harmony Benchmark Report on Cloud Database Servers [42] is used to verify the proposed algorithm. The report involved 18 Cloud Database Servers and each sever involved 10 QoS parameters. In the report [42], the 18×10 normalized decision matrix and the table of the relative importance of 10 QoS parameters were given, and the improved TOPSIS method was used to compute the compliance values and determine the trustworthiness of service providers. According to the method, the eleventh cloud service was evaluated as the most trustworthy service and the second cloud service was evaluated as the least trustworthy service.

In the following experiments, the algorithm of multi-attribute trusted cloud service selection proposed in this paper is used to rank cloud services given in the sample dataset. Suppose that $x_{ij}(1 \leq i \leq 18, 1 \leq j \leq 10)$ denotes the value of ith cloud service's jth attribute. The detailed process is given below.

First of all, data sets following the normal distribution $normrnd(x_{ij}, \delta)$ are generated. δ is set to 0.02 and attribute clouds of different cloud services are generated with the backward normal cloud generator. For the first three cloud services [42], their corresponding 10 attribute clouds are listed in Table 1. Then, based on the cloud hierarchical analysis, the weight coefficient cloud matrix of different attributes is generated (Table 2). Finally, the five-level standard trust cloud is selected and the improved fuzzy comprehensive evaluation method is used to compute the trust scores of different cloud services. The trust scores of 18 cloud servers are shown in Table 3.

CDS	Trust score	CDS	Trust score	CDS	Trust score
1	3.6654	7	4.6678	13	5.6016
2	2.5737	8	3.612	14	4.6012
3	3.6221	9	4.6043	15	4.5616
4	2.7738	10	2.6736	16	5.5227
5	4.6331	11	5.6397	17	5.5959
6	3.6667	12	4.590	18	5.6161

Compared with the improved TOPSIS method, the proposed algorithm gives the same cloud services with the maximum and minimum trustworthiness. However, the two algorithms are different in local ranking results because the proposed algorithm can measure QoS attributes of cloud services accurately, depict the fuzziness and inaccuracy of user preference precisely, and provide users with more accurate decision-making basis.

V. CONCLUSIONS AND FUTURE WORK

Cloud service selection belongs to the typical multi-attribute decision-making problems. In the selection process of cloud services, it is necessary to select trusted cloud services according to users' different demands. In this paper, the algorithm of multi-granularity standard trust cloud is proposed as the basis of judging the trust level of cloud services and the novel cloud service selection algorithm based on normal cloud model is given. Finally the feasibility of the algorithm is verified. The study provides a new way to solve the crisis of trust in the selection process of cloud services and is conducive to the promotion of cloud services.

In the future, we will establish an internet-based service sharing platform to gather the real service selection and usage data in different periods of time and design the self-adaptive computing model of describing the vagueness, inaccuracy and incompleteness of user preferences.

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RUI LIU was born in Xianyang, Shanxi, China, in 1996. She is currently pursuing the B.S. degree with the College of Information and Computer, Taiyuan University of Technology, China. Her research interests are computer network security and cloud computing.

YONGLE CHEN was born in Weifang, Shandong, China, in 1983. He received the B.S. degree from Jilin University in 2007, the M.S. degree from the Institute of Software, Chinese Academy of Science, in 2009, and the Ph.D. degree from the University of Chinese Academy of Sciences in 2013, all in computer science. From 2013 to 2015, he was an Assistant Professor with the College of Computer Science and Technology, Taiyuan University of Technology, Taiyuan, China, where he has been an Associate Professor since 2015. His research interests are wireless sensor networks, indoor positioning, and IoT security.
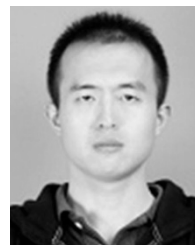
TONG LI received the B.S. degree in computer science and technology from the Taiyuan University of Technology in 2011, the M.S. degree in computer science and technology from the Beijing University of Technology in 2014, and the Ph.D. degree in information security from Nankai University in 2017. He is currently a Post-Doctoral Research with Guangzhou University. His research interests include applied cryptography and data privacy protection in cloud computing.

YULI YANG was born in Yicheng, Shanxi, China, in 1979. She received the M.S. degree in computer science and technology from Guangxi Normal University, China, in 2007, and the Ph.D. degree in computer science and technology from the Taiyuan University of Technology, Taiyuan, China, in 2015. She is currently a Lecturer with the College of Computer science and Technology, Taiyuan University of Technology. Her research interests are related with computer network security, cloud computing, and trust management.

YI TANG received the Ph.D. degree in applied mathematics from Sun Yat-sen University, Guangzhou. He is currently a Professor with the School of Mathematics and Information Science, Guangzhou University. His research interests include network security and database security.

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