FASTCloud: A framework of assessment and selection for trustworthy cloud service based on QoS

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Abstract

By virtue of technology and benefit advantages, cloud computing has increasingly attracted a large number of potential cloud consumers (PCC) plan to migrate traditional business to the cloud service. However, trust has become one of the most challenging issues that prevent the PCC from adopting cloud services, especially in trustworthy cloud service selection. In addition, due to the diversity and dynamic of quality of service (QoS) in cloud environment, the existing trust assessment methods based on the single constant value of QoS attribute and the subjective weight assignment are not good enough to provides an effective solution for PCCs to identify and select a trustworthy cloud service among a wide range of functionally-equivalent cloud service providers (CSP). To address the challenge, a novel assessment and selection framework for trustworthy cloud service, FASTCloud, is proposed in this study. This framework facilitate PCCs to select a trustworthy cloud service based on their actual QoS requirements. In order to accurately and efficiently assess the trust level of cloud services, a QoS-based trust assessment model is proposed. This model represents a trust level assessment method based on the interval multiple attributes with a objective weight assignment method based on the deviation maximization to adaptively determine the trust level of different cloud services provisioned by candidate CSPs. The advantage of proposed trust level assessment method in time complexity is demonstrated by the performance analysis

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and comparison.The experimental result of a case study with an open source dataset shows that the trust model is efficient in cloud service trust assessment and the FASTCloud can effectively help PCCs select a trustworthy cloud service.

1. Introduction

Cloud computing has become a new utilization paradigm of IT resources that provides web-based on-demand services to customers over the internet. Depending on the diverse business requirements of different IT customers, cloud computing offers a variety of service models including infrastructure-as-a-service, platform-as-a-service, software-as-a-service and etc. [1]. Compared with the traditional way of investing huge amounts of capital to purchase IT infrastructure, the economic benefits that cloud computing can bring to an enterprise by virtue of its technological advantages are obvious. Moreover, cloud computing also provides the basic platform for the rapid development of other emerging technologies, such as big data, 5G [2, 3], mobile edge computing and IoT [4]. In addition, cloud computing can free enterprises from the low-level task of building IT infrastructure so that they can focus more on the high-level task of business innovation to create value for their customers. Therefore, more and more organizations and individuals have been experimenting with building business applications on the cloud and making it more agile by adopting flexible and resilient cloud services.

However, it is not easy for the potential cloud customers (PCC), such as enterprises, organizations and individuals that plan to adopt cloud service, to take full advantage of cloud computing [5]. Enterprises will face many challenges in migrating applications, workflow and business from traditional IT systems to the cloud platform. These challenges are often related to the specific requirements and characteristics of the existing business of customers, which depend heavily on the quality of service (QoS) of the cloud service provisioned by cloud service

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provider (CSP) [6]. Moreover, with the increasing demands of customers, a large number of cloud services with similar functions and features provided by various CSPs have emerged in the cloud business market. Different cloud services can satisfy the multiple requirements of different cloud service customers (CSC) for QoS. Therefore, it has truly brought about a tough challenge for PCCs to select a trustworthy CSP out of a large pool of candidate CSPs with similar offerings [7]. That is, how to accurately and objectively assess the service quality level of cloud services provided by different CSPs has become one of the most challenging issues for PCCs.

To address these issues related to trust, various researches on QoS-based cloud service trust assessment have attracted considerable interest. These studies focus on evaluating the trustworthiness or trust level of different CSPs by leveraging multiple QoS attributes related to their cloud services. The trustworthiness or trust level is a quantitative value, which is often considered as a comprehensive service capability of a CPS for provisioning the cloud service. However, the feasibility of QoS information acquisition mechanisms and the accuracy and efficiency of trust assessment methods are still urgent issues to be solved in the research on QoS-based trust assessment and selection of trustworthy cloud service.

In order to address these issues effectively, we propose a novel assessment and selection framework (FASTCloud) for trustworthy cloud services for enhancing the feasibility of QoS information acquisition mechanism. Furthermore, a QoS-based trust assessment model is proposed to improve the accuracy and efficiency of trust assessment method. The main target of FASTCloud is to facilitate PCCs to select a trustworthy cloud service based on their actual QoS requirements through the trust assessment of cloud services. Following are the prime contributions of the present research work.

- A novel assessment and selection framework for trustworthy cloud services based on diverse and dynamic QoS, FASTCloud, is proposed. The FAST-Cloud collects QoS information of various cloud services, which are from

static agreed values and dynamic monitoring values regarding these QoS submitted by CSPs and CSCs respectively.

- For the convenience of PCCs to select a trustworthy cloud service, a trustworthy cloud servcie selection component is designed in FASTCloud to accept assessment requests initiated by PCCs. This component takes the QoS attributes specified in the assessment request of a PCC as metrics and takes the candidate CSPs matched against these metrics as objects to be assessed. The component utilizes the collected information about QoS attributes to assess cloud services and return assessment results to PCCs.

- To accurately and efficiently assess the trust level of cloud services, a QoS-based trust assessment model is proposed and implemented by the component. This model presents a trust assessment method based on the QoS attribute represented in the form of interval value to determine the trust level of cloud services of candidate CSPs. In order to objectively determine weights to different QoS attributes, a weight assignment method based on the deviation maximization is adopted in the model.

- An experiment is conducted in the form of case study on an open dataset to validate the feasibility and availability of FASTCloud. The experimental result shows that the proposed framework is effective in cloud service trust assessment and help PCCs select a trustworthy CSP. The performance of trust level assessment method proposed in this model is analysed in terms of time complexity and simulation experiment. The performance advantage of the proposed method is illustrated by comparing with other cloud service assessment methods.

The rest of the paper is organized as follows. Section 2 discusses the related work. Section 3 introduces the proposed framework. Section 4 details the proposed cloud service trust assessment model and elaborates on the presented trust level assessment method. Section 5 presents the experiments and analysis. Section 6 presents the conclusions of this paper and outlines directions for future

work.

2. Related work

In recent years, study on assessment and selection of trustworthy cloud service has attracted considerable interest of many researchers. A variety of trust assessment methods and trust models have been proposed by taking QoS attributes as metrics. Sun et al. [8] proposed a cloud service selection with criteria interactions framework (CSSCI) for cloud service selection. This framework applies a fuzzy measure and choquet integral to measure and aggregate non-linear relations between criteria, such as latency, response time and availability. Jatoth et al. [9] proposed a methodology to addresses a hybrid multi-criteria decision-making model involving the selection of cloud services among the available alternatives. This methodology assigns various ranks to cloud services based on the quantified QoS parameters using a novel extended grey TOPSIS integrated with analytical hierarchical process (AHP). In [10], three multiple criteria decision making (MCDM)-based multi-dimensional trust assessment schemes have been presented, which assess trustworthiness of CSPs by monitoring compliance provided by CSPs against the set SLAs. These schemes adopt three MCDM methods (AHP, TOPSIS and PROMETHEE) respectively that enable CSCs to determine the trustworthiness of a CSP from different perspectives. [11] proposed a personalized QoS ranking prediction framework for cloud services, which identifies and aggregates the preferences between pairs of cloud services to produce a ranking of them by taking advantage of the past usage experiences of other users. Li and Du [12] presents an adaptive trust management model for CSCs to select a more trustworthy CSP. This model is used to assess the competence of cloud services by analysing the history information related to multiple QoS attributes of the SLA contracted by CSC and CSP. In [13], a novel method was presented, which employed a multi-QoS-aware cloud service selection strategy and the analytic hierarchy process (AHP) method to help the CSCs to select the appropriate cloud service.

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In addition, there are many researchers tend to adopt the service measurement index (SMI) defined by the Cloud services measurement initiative consortium [14] as QoS attributes for assessment and selection of cloud services. The SMI is one of the widely accepted metrics for quality measurement of cloud service. Singh and Sidhu [15] proposed a compliance-based multi-dimensional trust assessment system, which enabled CSCs to determine the trustworthiness of a CSP. This system helps CSCs select a CSP from candidate CSPs that satisfy its desired QoS requirements. Somu et al. [16] presented a trust-centric approach for identification of suitable and trustworthy CSPs. This approach employs multiple algorithms for the identification of similar service providers, credibility based trust assessment, selection of trustworthy service providers, and optimal service ranking respectively. A trust assessment framework that uses the compliance monitoring mechanism to determine the trustworthiness of CSPs was proposed in [17]. The compliance values are computed and then processed using a technique known as the improved technique for order of preference by similarity to ideal solution (TOPSIS) to obtain trustworthiness of CSPs. In [18], a SMI-based framework was designed to measure all the QoS attributes and rank the Cloud services based on these attributes. This framework employed an AHP based ranking mechanism which can assess the cloud services based on the QoS requirements of CSCs. Tripathi et al. [19] proposed an improved SMI-based framework for enabling CSCs to select an appropriate CSP according to their QoS requirements. This framework employed the analytic network process (ANP) method for the ranking of cloud services. Yadav and Goraya [20] proposed a novel two-way ranking based cloud service mapping framework for CSCs to select a suitable CSP. In this framework, AHP has been used to assess the ranking score of both the CSPs and CSCs by considering the QoS attributes value offered by them as well as desired by their counterpart. Although some researchers have tried to improve the credibility of cloud services by solving the underlying infrastructure security problems, such as physical security authentication [21] and wireless device secure access[22, 23], these methods cannot be clearly perceived and adopted by PCCs in selecting the trustworthy CSP.

As aforementioned, there are two deficiencies in the existing studies. On the one hand, existing studies usually use the open sources or monitoring tools to actively collect information related to the QoS attributes of different CSPs for the cloud services trust assessment. The former is a time-consuming and laborious task, and the information collected may be incomplete and inaccurate because of lack of timely update. In addition, CSPs may exaggerate the QoS of their cloud services to attract more PCCs for the profits. The latter attempt to collect QoS information by monitoring the cloud platforms from different dimensions (e.g., service side or client side of cloud platform). Due to the impact on performance and security of cloud platform, it applies only to CSC monitoring QoS statue of their own cloud-based , not to multi-customers in the same cloud or different customers in different cloud.

On the other hand, existing researchers usually employ the single and constant value of QoS attribute (e.g., the agreed service level objective (SLO) regarding QoS attribute in the service level agreement (SLA) contracted by CSP and CSC) of cloud services to assess the trustworthiness or trust level of CSPs. In fact, even for the same cloud service and the same QoS attribute, different CSCs may have different QoS and SLO requirements. Then, a CSP must be capable of providing cloud service with various QoS attributes having different SLOs for its CSCs. Moreover, most of the existing researches adopt subjective based weighting approach to assign weights for QoS attributes. This approach does not apply to most general evaluators who have no expertise and experience in the field of cloud assessment. Therefore, the existing trust assessment methods are not well adopted to the running state of cloud environment in a real-world scenario, in which the QoS are dynamic and fluctuant continuously.

To the best of our knowledge, there is still a lack of effective solutions to tackle with the above issues. Contrary to this, a novel assessment and selection framework for trustworthy cloud service and a trust assessment model are proposed to effectively solve these issues, which will be detailed as follows.
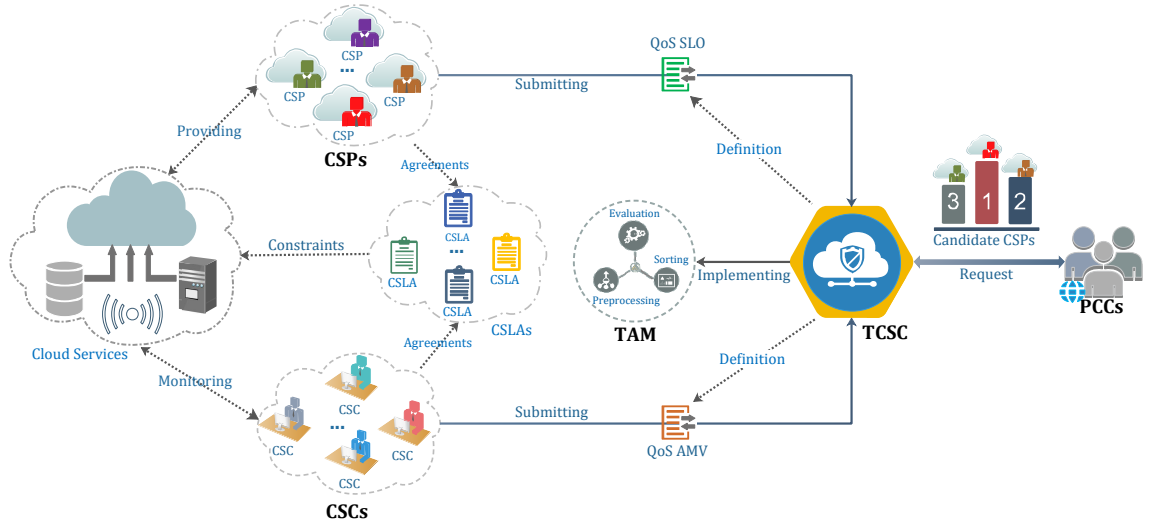
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Figure 1: The proposed framework: FASTCloud.

3. The Proposed Framework

This section proposes a assessment and selection framework for trustworthy cloud service (FASTCloud), which is an extension base on our previous works [24]. The FASTCloud collects information related to QoS attributes of different cloud services from CSPs and CSCs respectively, and utilizes trust assessment model to assess the trust level of cloud services accordingly. The QoS attributes provided by CSPs and CSCs are determinded and contracted in SLA. This framework will be detailed in the followings.

The FASTCloud mainly consists of three entities and a trustworthy cloud servcie selection component (TCSC), as shown in figure 1. The main entities in FASTCloud are CSPs, CSCs and PCCs. TCSC is responsible for evaluating trust level of cloud services based on the collected QoS attributes information by employing the trust assessment model, and returning the trust assessment results to PCCs. The specific roles and responsibilities of entities are as follows.

- **CSP** signs a CSLA with its CSC on the specific SLO of QoS attributes of the cloud service. CSP operates and maintains cloud services to its CSC in accordance with the CSLA. In addition, CSP provides TCSC with SLO

of QoS attributes of its cloud service according to the CSLA.

- **CSC** signs a CSLA with its CSP on the specific SLO of QoS attributes of the cloud service according to QoS requirements of its actual business. Furthermore, CSC monitors the QoS attributes according to the CSLA and provides actual monitoring value (AMV) to TCSC during the cloud service runtime.

- **PCC** is a requester for a cloud service assessment, that is, a customer planning to purchase and use a cloud service. PCC initiates an assessment request to TCSC based on its QoS requirements and receives assessment results from TCSC (i.e., candidate CSPs), and selects the most trustworthy one among them.

The main role of TCSC is to collect QoS attributes information provided by CSP and CSC (i.e., SLO and AMV) and to assess cloud services. According to the assessment request of PCC and the collected QoS attributes information, TCSC utilizes the trust assessment model (will be detailed later) to assess the trust level of cloud services. Then, TCSC offers the trust assessment results to PCC so that it can select a trustworthy cloud service. The functions and activities of TCSC will be described as follows.

1. CSPs submit SLOs of QoS attributes to TCSC. According to the CSLA signed with different CSCs, a CSP provides TCSC with SLO of QoS attributes of the cloud service in the form of a uniform specification (e.g., a standard template defined by TCSC). The time with which the CSP provides SLOs of QoS attributes is determined by the frequency of changes in the content of the CSLA. For instance, each time a CSP signs a CSLA with a new CSC or makes a change (e.g., addition, deletion, or modification) to an existing CSLA, it shall provide TCSC with the latest SLOs of QoS attributes of the cloud service.

2. CSCs submit AMVs of QoS attributes to TCSC. In accordance with the CSLA signed with a CSP, a CSC continuously monitors the QoS at-

tributes. CSC then provides TCSC with AMV of QoS attributes of the cloud service in the form of a uniform specification (e.g., a standard template defined by TCSC). Since the monitoring tools or services used by different CSCs are various, the time with which the CSC provides AMVs of QoS attributes is determined by itself. In order to improve the feasibility of AMVs collection, the CSC shall satisfy the principle of minimum submission frequency stipulated by TCSC (e.g., at least once a day).

3. PCCs initiate a trust assessment request to TCSC for a trustworthy cloud service. When a PCC initiates a trust assessment request along with QoS requirements to TCSC, then TCSC would match the QoS requirements of PCC with the QoS attributes information provided by CSPs and find a list of candidate cloud services which satisfy the QoS requirements of PCC. The TCSC uses the trust assessment model to assess the trust level of the candidate cloud services, and offers a ranked list of trustworthy CSPs to the PCC.

In fact, compared with the traditional service-oriented computing environment, QoS attributes information in cloud environment is easier to obtain [11]. Since most CSPs are generally able to provide monitoring tools/services with free or paid for CSCs to monitor QoS status of their cloud services (e.g., the AWS CloudWatch, Microsoft Azure Monitor, Huawei Cloud Eye and etc.), CSCs can easily acquire the actual value of QoS attributes. Therefore, we assumes that the monitoring tools/services provided by CSPs are trustworthy, so that the actual values of QoS attributes monitored and acquired by CSCs are true. Thus, the AMVs of QoS attributes submitted by CSCs are reliable. In addition, there are also many mature applications and tools (e.g., Web-based interactive online information collection, questionnaire and etc.) that can facilitate TCSC to collect the QoS attributes information provided by CSPs and CSCs.

Therefore, the technical implementation details related to the specific monitoring and collection of QoS attributes information beyond the research scope of this paper, which would not be discussed further. The rest focuses on the

trust assessment model of TCSC, which will be elaborated.

4. The Trust Assessment Model

The trust assessment model (TAM) proposed in this section uses the QoS attributes information collected by TCSC to assess the trust level of cloud services provided by different CSPs. The quantitative values representing the trust level of CSPs can be obtained by TAM, so as to help PCCs select a trustworthy cloud service based on their QoS requirements.

4.1. Model Definition

Let $C = \{c_i | 1 \leq i \leq I\}$ denote the set of CSPs that provide cloud service to CSCs. Let $U = \{u_{ij} \in U_i | 1 \leq i \leq I, 1 \leq j \leq J\}$ denote the set of CSCs that employ cloud service, where U_i represents the set of CSCs which employ the cloud service of the ith CSP, u_{ij} represents the jth CSC of the ith CSP. Let $A = \{a_k | 1 \leq k \leq K\}$ denote the set of QoS attributes of cloud services with the same function and service pattern. Let $S = \{s_{ij}(a_k)\}$ denote SLO of the kth QoS attribute agreed by the ith CSP and its jth CSC. Let $Q = \{q_{ij}(a_k) | 1 \leq i \leq I, 1 \leq j \leq J, 1 \leq k \leq K\}$ denote the kth QoS attribute monitored by the jth CSC of the ith CSP.

4.2. Normalized Processing of QoS Information

For convenience of description, we take the QoS attributes (denote as a_k, $a_k \in A$) of the cloud service provided by a specific CSP (denote as c_i, $c_i \in C$) and its CSCs (denote as u_{ij}, $u_{ij} \in U_i$) as an example to elaborate the normalized processing of QoS information of TAM. The CSP c_i submits the SLO $s_{ij}(a_k)$ of a QoS attribute a_k to TCSC. The CSC u_{ij} submits the AMV $q_{ij}(a_k)$ of a QoS attribute a_k to TCSC.

According to the SLO $s_{ij}(a_k)$ of each QoS attribute submitted by c_i, the SLOs of all QoS attributes can be obtained by TCSC, denoted as $\boldsymbol{S_i(A)}$. It can be represented as:

$$\boldsymbol{S_i(A)} = \begin{bmatrix} s_{i1}(a_1) & s_{i1}(a_2) & \cdots & s_{i1}(a_k) \\ s_{i2}(a_1) & s_{i2}(a_2) & \cdots & s_{i2}(a_k1) \\ \vdots & \vdots & \ddots & \vdots \\ s_{ij}(a_1) & s_{ij}(a_2) & \cdots & s_{ij}(a_k) \end{bmatrix} \tag{1}$$

where, $s_{ij}(a_k)$ $(s_{ij}(a_k) \in S)$ denotes the SLO of kth QoS attribute agreed by c_i and its jth CSC.

Similarly, the AMVs of all QoS attributes can be obtained by TCSC on the basis of the AMV $s_{ij}(a_k)$ of each QoS attribute monitored and submitted by u_{ij}, which is denoted as $\boldsymbol{Q_i(A)}$. It can be represented as:

$$\boldsymbol{Q_i(A)} = \begin{bmatrix} q_{i1}(a_1) & q_{i1}(a_2) & \cdots & q_{i1}(a_k) \\ q_{i2}(a_1) & q_{i2}(a_2) & \cdots & q_{i2}(a_k) \\ \vdots & \vdots & \ddots & \vdots \\ q_{ij}(a_1) & q_{ij}(a_2) & \cdots & q_{ij}(a_k) \end{bmatrix} \tag{2}$$

where, $q_{ij}(a_k)$ $(q_{ij}(a_k) \in Q)$ denotes the average AMV of the kth QoS attribute monitored by u_{ij}.

Since different CSCs have various monitoring frequencies for QoS attributes, the average AMV of each QoS attribute submitted by CSC is taken as the actual monitoring value. Assuming that u_{ij} submits N times $q_{ij}(a_k)$, its average AMV can be calculated by the following equation:

$$q_{ij}(a_k) = \frac{\sum_{n=1}^{N} q_{ij}(a_k)^n}{n} \tag{3}$$

where, $q_{ij}(a_k)^n$ represents the nth AMV of the kth QoS attribute monitored and submitted by u_{ij}. It should be noted that the frequency N of a AMV $q_{ij}(a_k)$ submitted by different u_{ij} could be different value.

In addition, in order to obtain the real SLO that a QoS attribute of the cloud service provided by a CSP can achieve at run time, we give the following definition of consistency. That is,

Definition 1. *For a given QoS attribute a_k, if its SLO $s_{ij}(a_k)$ submitted by the CSP c_i is not less than its AMV $q_{ij}(a_k)$ submitted by the CSC u_{ij}, then it is considered that the cloud service provided by the CSP c_i satisfy consistency on the the QoS attribute a_k.*

In a real cloud environment, QoS attributes can be divided into two types according to their features: benefit and cost. The benefit QoS attribute refers to that the higher the value of attribute is, the higher its performance or capability is (e.g., throughput and availability). The cost QoS attribute refers to that the higher the value of attribute is, the lower its performance or capability is (for example, packet loss rate, response time). Therefore, the formal definition is as follows:

Definition 2. *For the given benefit QoS attribute a_k, the cloud service provided by CSP c_i satisfies the condition of consistency is: $q_{ij}(a_k) \geq s_{ij}(a_k)$. While for the given cost QoS attribute a_k, the cloud service provided by CSP c_i satisfies the condition of consistency is: $q_{ij}(a_k) \leq s_{ij}(a_k)$.*

In accordance with the definition of consistency and the SLOs $\boldsymbol{S_i(A)}$ and the AMVs $\boldsymbol{Q_i(A)}$ of QoS attributes A, the consistency rate of the cloud service provided by c_i on the QoS attributes A can be determined, denoted as $\boldsymbol{\Lambda} = [\lambda_{i1}, \lambda_{i1}, \cdots, \lambda_{ik}]$. λ_{ik} represents the consistency rate of the cloud service of c_i on the kth QoS attribute, which can be calculated as follows:

$$\lambda_k = \frac{N_i(a_k)}{|U_i(a_k)|} \tag{4}$$

where, $N_i(a_k)$ represents the total number that the cloud service of c_i satisfies the consistency condition on the kth QoS attribute. $|U_i(a_k)|$ represents the number of CSCs agreed on SLO of the kth QoS attribute with c_i (i.e., the number of elements in the kth column of $\boldsymbol{S_i(A)}$). Hence, it can be seen that $N_i(a_k) \leq |U_i(a_k)|$ and $0 \leq \lambda_{ik} \leq 1$.

For the benefit QoS attribute, $N_i(a_k)$ can be calculated by the following equation.

$$N_i(a_k) = \begin{cases} \sum_{j=1}^{|U_i(a_k)|} 1, & q_{ij}(a_k) \geq s_{ij}a(k) \\ \\ 0, & others \end{cases} \tag{5}$$

For the cost QoS attribute, $N_i(a_k)$ is as follows.

$$N_i(a_k) = \begin{cases} \sum_{j=1}^{|U_i(a_k)|} 1, & q_{ij}(a_k) \leq s_{ij}a(k) \\ \\ 0, & others \end{cases} \tag{6}$$

The minimum and maximum SLO of each QoS attribute related to the cloud service of c_i can be obtained from $S_i(A)$, denoted as $s_i(a_k)^l$ and $s_i(a_k)^u$ respectively. Then the SLO of QoS attributes of the cloud service provided by c_i can be expressed as the interval value: $s_i(\tilde{a}_k) = \left[s_i(a_k)^l, s_i(a_k)^u \right]$. It represents the SLO extent of QoS attribute a_k claimed by the CSP c_i to its CSCs U_i that its cloud service can achieve. However, in the real scenario, the SLO extent of QoS attribute a_k that the CSP c_i can achieve in its cloud service is determined by the consistency rate of the QoS attribute. Therefore, the actual SLO extent of QoS attributes A that the CSP c_i is capable of offering to its CSCs in the cloud service, denoted as $\tilde{b}_{ik}$, can be obtained by multiplying the SLO interval value $s_i(\tilde{a}_k)$ and its consistency rate λ_{ik}. That is,

$$\tilde{b}_{ik} = \lambda_{ik} \times s_i(\tilde{a}_k) = \left[\lambda_{ik} s_i(a_k)^l, \lambda_{ik} s_i(a_k)^u \right] = \left[b_{ik}^l, b_{ik}^u \right] \tag{7}$$

where, b_{ik}^l and b_{ik}^u respectively denote the actual minimum and maximum SLO of the kth QoS attribute.

Thus, the actual SLO of all QoS attributes A that the CSP c_i is capable of offering to its CSCs can be denoted as $\boldsymbol{\tilde{b}_i} = \left[\tilde{b}_{i1}, \tilde{b}_{i2}, \cdots, \tilde{b}_{ik} \right]$.

4.3. Trust Level Evaluation Method

Assuming that a PCC issues an assessment request with K QoS attributes to TCSC. According to the assessment request, I candidate CSPs whose cloud service could meet the requirement of QoS attributes would be found in TCSC.

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Then, TCSC employs TAM to obtain the actual SLO interval value of K QoS attributes of the I CSPs and assesses the trust level of CSPs accordingly. The trust level assessment method comprises five steps described as follows.

4.3.1. Construct the normalized decision matrix

According to equations (3-1) - (3-7), the actual SLO interval value of the K QoS attributes of the I CSPs can be obtained. The decision matrix used to assess the trust level of the I CSPs can be constructed on the basis of their actual SLO interval value, denoted as $\boldsymbol{B} = (\tilde{b}_{ik})_{I \times K}$. That is,

$$
\boldsymbol{B} = \left[\tilde{\boldsymbol{b_1}}, \tilde{\boldsymbol{b_2}}, \cdots, \tilde{\boldsymbol{b_i}}, \cdots, \tilde{\boldsymbol{b_I}}\right]^T =
\begin{bmatrix}
\tilde{b}_{11} & \tilde{b}_{12} & \cdots & \tilde{b}_{1k} \\
\tilde{b}_{21} & \tilde{b}_{22} & \cdots & \tilde{b}_{2k} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{b}_{i1} & \tilde{b}_{i2} & \cdots & \tilde{b}_{ik} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{b}_{I1} & \tilde{b}_{I2} & \cdots & \tilde{b}_{IK}
\end{bmatrix}
\tag{8}
$$

Due to different QoS attributes may belong to different types (benefit and cost) and have different dimensions (i.e., measurement benchmark), there is a lack of comparability between them. In order to eliminate the impact of these problems on the trust assessment results, the decision matrix $\boldsymbol{B}$ needs to be normalized.

Let E_1 and E_2 denote the benefit type and cost type respectively. The normalized decision matrix $\boldsymbol{B}$ can be denoted as $\boldsymbol{R} = (r_{ik})_{I \times K}$. r_{ik} is also a interval number, denoted as $r_{ik} = \left[r_{ik}^l, r_{ik}^u\right]$, where r_{ik}^l and r_{ik}^u can be represented as follows:

$$
r_{ik}^l = \begin{cases}
b_{ik}^l \big/ \sum_{i=1}^{I} b_{ik}^u \\
(1/b_{ik}^u) \big/ \sum_{i=1}^{I} (1/b_{ik}^l)
\end{cases}
\tag{9}
$$

$$
r_{ik}^u = \begin{cases}
b_{ik}^u \big/ \sum_{i=1}^{I} b_{ik}^l \\
(1/b_{ik}^l) \big/ \sum_{i=1}^{I} (1/b_{ik}^u)
\end{cases}
\tag{10}
$$

4.3.2. Determine the objective weights of QoS attributes

It is worthy considering that the status of QoS attributes would fluctuate dynamically during the running time of cloud service in the real cloud context [25]. actual operation process. However, most of the existing researches on cloud service trust assessment employs the subjective preference based weight assignment method to determine the weights of QoS attributes [7, 6, 5, 26]. The weights of QoS attributes obtained by the subjective method are static constants, which cannot well adapt to the dynamic features of QoS in the real cloud context. Thus the accuracy of trust assessment results would inevitably be affected.

Therefore, in order to alleviate the above issue, a objective weight assignment method based on the deviation maximization is adopted to determine the weights of QoS attributes. The principle behind this method is that if the difference of attribute values of all CSPs on a Qos attribute is smaller, it indicates that the impact of this Qos attribute on trust assessment is smaller. On the contrary, if a attribute can make the difference of attribute values of all CSPs significantly different, it indicates that this Qos attribute will play an important role in the trust assessment. In particular, if the attribute values of all CSPs on a QoS attribute have no difference, it indicates that this QoS attribute will have no impact on the trust assessment. The specific process of this method are as follows.

Supposing that within a given assessment period, let $\boldsymbol{\omega} = (\omega_1, \omega_2, \cdots, \omega_k, \cdots, \omega_K)$ be the weight vector of QoS attributes A, where $\omega_k \geq 0$ and conforms to the following constraint.

$$\sum_{k=1}^{K} \omega_k^2 = 1 \tag{11}$$

Let $d(r_{ik}, r_{fk}) = \|r_{ik} - r_{fk}\|$ be the degree of separation between elements r_{ik} and r_{fk} in the normalized matrix $\boldsymbol{R}$, where $\|r_{ik} - r_{fk}\| = |r_{ik}^l - r_{fk}^l| + |r_{ik}^u - r_{fk}^u|$. For a given QoS attribute a_k $(a_k \in A)$, let $D_{ik}(\boldsymbol{\omega})$ denote the deviation of CSP c_i from other CSPs. It can be represented as follows:

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$$D_{ik}(\boldsymbol{\omega}) = \sum_{f=1}^{I} \|r_{ik} - r_{fk}\| \omega_k = \sum_{f=1}^{I} d(r_{ik}, r_{fk})\omega_k \tag{12}$$

where, $1 \le i \le I$ and $1 \le k \le K$.

In addition, let $D_k(\boldsymbol{\omega})$ denote the total deviation of each CSP from other CSPs on the given QoS attribute a_k, which can be represented as follows:

$$D_k(\boldsymbol{\omega}) = \sum_{i=1}^{I} D_{ik}(\boldsymbol{\omega}) = \sum_{i=1}^{I} \sum_{f=1}^{I} d(r_{ik}, r_{fk})\omega_k \tag{13}$$

Based on the above principle, the weight vector of QoS attributes $\boldsymbol{\omega}$ should make the total deviation of all CSPs on all QoS attributes. For this purpose, the objective function is constructed as follows.

$$max\,(D(\boldsymbol{\omega})) = \sum_{k=1}^{K} D_k(\boldsymbol{\omega}) = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{f=1}^{I} d(r_{ik}, r_{fk})\omega_k \tag{14}$$

Thus, the calculation of the weight vector of QoS attributes $\boldsymbol{\omega}$ is equivalent to solving the optimal solution of equation (14) under the constraints of equation (11). It can be solved by the method presented in literature [27] and denoted as follows.

$$\omega_k = \frac{\sum_{i=1}^{I} \sum_{f=1}^{I} d(r_{ik}, r_{fk})}{\sqrt{\sum_{k=1}^{K} \left(\sum_{i=1}^{I} \sum_{f=1}^{I} d(r_{ik}, r_{fk})^2 \right)}} \tag{15}$$

Since the traditional weight vector generally conforms to the normalization constraint, ω_k need to be normalized. That is,

$$\omega_k = \frac{\sum_{i=1}^{I} \sum_{f=1}^{I} d(r_{ik}, r_{fk})}{\sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{f=1}^{I} d(r_{ik}, r_{fk})} \tag{16}$$

4.3.3. Calculate the trust level of CSP

In this paper, we represent the integrated value of CSP c_i on all QoS attributes as its trust level, which can be denoted as $z_i(\boldsymbol{\omega})$. It can be obtained by aggregating the element r_{ik} of the normalized decision matrix $\boldsymbol{R}$ with the weight λ_k of QoS attribute in the weight vector $\boldsymbol{\omega}$.

$$z_i(\boldsymbol{\omega}) = \sum_{k=1}^{K} \omega_k r_{ik} \qquad (17)$$

4.3.4. Construct the possibility degree matrix

Since the trust level of the CSP $z_i(\boldsymbol{\omega})$ is still a interval number, it is not easy to rank the cloud services of CSPs directly. Therefore, possibility degree comparison approach is used to rank the $z_i(\boldsymbol{\omega})$. According to [28], formal definition of possibility degree is as follows:

Definition 3. *If both $\tilde{a}$ and $\tilde{b}$ are interval numbers, or one of them is interval number, let them be $\tilde{a} = [a^l, a^u]$ and $\tilde{b} = [b^l, b^u]$. Let l_a and l_b be denoted as $a^u - a^l$ and $b^u - b^l$, then the possibility degree of $\tilde{a} \geq \tilde{b}$ can be represented as follow.*

$$p(\tilde{a} \geq \tilde{b}) = \frac{min\left\{l_a + l_b, max(a^u - b^l, 0)\right\}}{l_a + l_b} \qquad (18)$$

For the given CSP c_i and CSP c_e, let $z_i(\boldsymbol{\omega})$ and $z_e(\boldsymbol{\omega})$ denote the integrated value of them on all QoS attribute. Let $p(z_i(\boldsymbol{\omega}) \geq z_e(\boldsymbol{\omega}))$ denote the possibility degree of of them, which can be represented as p_{ie} $(1 \leq i, e \leq I$ and $i \neq e)$ for short. Then, the possibility degree matrix that contains the possibility degree of pairwise comparison between all CSPs can be constructed on the basis of the above definition and equation, denoted as $P = (p_{ie})_{I \times I}$. Thus, the ranking problem of interval numbers is transformed into the ordering vector problem of the possible degree matrix, which is described below.

4.3.5. Rank the cloud services of CSPs

Let $\boldsymbol{v} = (v_1, v_2, \cdots, v_i, \cdots, v_I)$ be the ordering vector of the possible degree matrix $\boldsymbol{P}$. According to [28], the equation of ordering vector is as follows:

$$v_i = \frac{1}{I(I-1)} \left(\sum_{e=1}^{I} p_{ie} + \frac{I}{2} - 1 \right) \qquad (19)$$

According to v_i, the priority of cloud services of all CSPs in satisfying QoS requirements of the PCC can be obtained by ranking $z_i(\boldsymbol{\omega})$. Then, PCCs can

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Algorithm 1 Trust Level Evaluation Algorithm

Input: The QoS attributes A specified by PCC.
Output: The priority ranking of candidate CSPs υ.
1: Matching the candidate CSPs set C with QoS attributes A.
2: **for** each CSP $c_i \in C$ **do**
3:     Extracting the SLO set $S_i(A)$ submitted by c_i on A;
4:     Extracting the AMV set $Q_i(A)$ submitted by the CSCs of c_i on A;
5:     Calculating the actual SLO interval $b_i(A)$ according to $S_i(A)$ and $Q_i(A)$;
6: **end for**
7: Constructing the decision matrix B with $b_i(A)$;
8: **for** each $b_i(A) \in B$ **do**
9:     Normalizing $b_i(A)$ to $r_i(A)$ according to the type of a_k.
10: **end for**
11: Constructing the normalized decision matrix R with $r_i(A)$;
12: **for** each $r_i(A) \in R$ and each $a_k \in A$ **do**
13:     Calculating the deviation $D_{ik}(\omega)$ of c_i on a_k;
14: **end for**
15: **for** each $c_i \in C$ **do**
16:     Calculating the total deviation $D_A(\omega)$ of c_i on a_k;
17: **end for**
18: Determing the weight vector ω of A by solving the optimal problem that maximizes $D_A(\omega)$;
19: Obtaining the trust level Z of C by aggregating R with ω;
20: **for** each $z_i \in Z$ **do**
21:     Calculating the possibility degree p_i of z_i;
22: **end for**
23: Constructing the possibility degree matrix P with p_i;
24: Calculating the ordering vector υ of P;
25: **return** υ;

Table 1: Definition of QoS attributes[29]

QoS attributes	Abbreviation	Unit	Type	Definition
Availability	av	%	B	Number of successful invocations/total invocations
Throughput	th	invokes/s	B	Total Number of invocations for a given period of time
Successability	su	%	B	Number of response/number of request messages
Reliability	re	%	B	Ratio of the number of error messages to total message
Latency	la	ms	C	Time taken for the server to process a given request
Response Time	res	ms	C	Time taken to send a request and receive a response

select the most trustworthy should service based on the ranking results. Algorithm 1 illustrates the trust level assessment process.

5. Experiment and Analysis

We have conducted a simulation experiment of a case study by using an open source dataset to validate the availability of TAM.

5.1. Experiment Setup

There is currently no available dataset for the experiment. Therefore, we use a web services dataset from the real-world to validate the availability of TAM. The dataset, named as QWS[29], consists of 2,507 pieces of real data produced by hundreds of Web services on the 6 QoS attributes. The definitions of QoS attributes contained in QWS are shown in Table I, where B and C in the type column represent the benefit and cost respectively.

Figure 2 shows the distribution of QoS attributes values of QWS dataset. As can be seen from Figure 2, the distributions of the QoS attributes values are different, where the distributions of availability, successability, latency and response Time are relatively centralized, while the distributions of throughput and reliability are relatively scattered. In fact, different Web services of QWS contain different amounts of QoS attribute value. For instance, some Web services contain only a value set of QoS attributes (the 6 QoS attributes values represented as a value set), while some Web services contain multiple value sets of QoS attributes. Moreover, there are small number of Web services contain some outliers on the QoS attributes. Therefore, in order to focus on the details
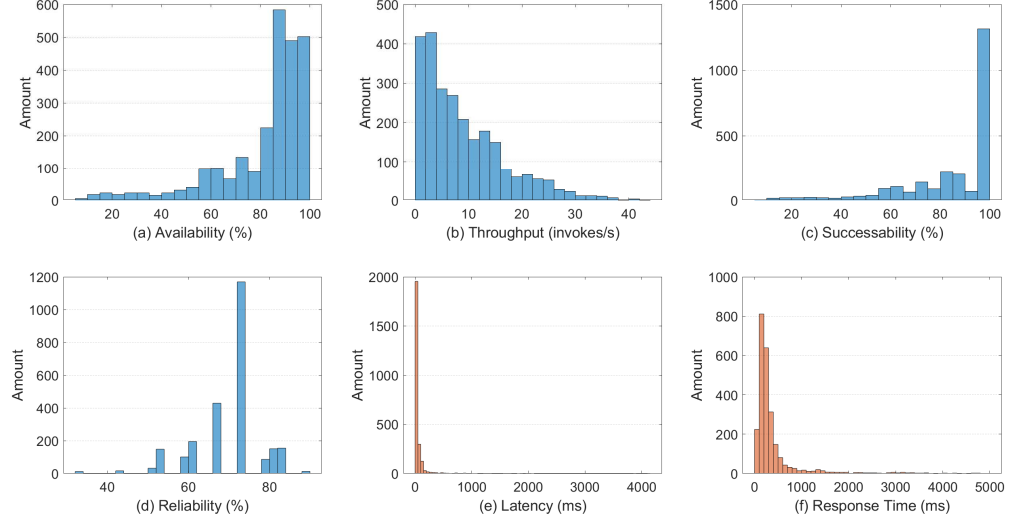
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Figure 2: The QoS distribution statistic of QWS.

of cloud service trust level assessment method, this experiment simplifies the information processing process of QoS attributes in TAM (as aforementioned in subsection 3.3.2) and presents the following case study.

5.2. Case Study

Suppose that a PCC initiates an assessment request to TCSC and specifies the SLO requirements interval on QoS attributes of cloud services according to the distribution of QoS attributes values in the QWS (i.e., Figure 2), as showed in Table II. Since it is difficult to obtain the real SLOs on QoS attributes of cloud services provided by CSPs in the real scenario, the SLO interval values of QoS attributes in Table II are taken as the agreed SLO of CSPs and CSCs. The QWS dataset is used as the AMV on the QoS attributes of cloud services submitted by the CSCs of these CSPs. In addition, assume that TCSC matched 5 candidate CSPs satisfy the SLO requirements of the PCC according to its assessment request, denoted as CSP_1, CSP_2, CSP_3, CSP_4 and CSP_5. The maximum and minimum values of these candidate CPSs on each QoS attribute are taken as their actual SLO interval, as shown in Table III.

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Table 2: The SLO interval of each QoS attributes specified by PCC

QoS attributes	SLO	
	Minimum	Maximum
av	50	100
th	1	35
su	50	100
re	50	100
la	1	100
res	50	300

Table 3: The actual SLO interval value of CSPs on the QoS attributes

$CSPs$	QoS Attributes					
	av	th	su	re	la	res
CSP_1	[87, 96]	[6, 23]	[95, 98]	[58, 73]	[8, 33]	[103, 204]
CSP_2	[62, 97]	[9, 32]	[63, 99]	[56, 83]	[9, 29]	[113, 246]
CSP_3	[61, 92]	[4, 26]	[60, 93]	[62, 69]	[7, 27]	[89, 215]
CSP_4	[71, 78]	[5, 30]	[72, 85]	[59, 67]	[6, 31]	[124, 198]
CSP_5	[70, 81]	[7, 21]	[69, 82]	[63, 74]	[8, 26]	[92, 193]

Figure 3: The normalized decision matrix of candidate CSPs

$$\boldsymbol{R} = \begin{pmatrix} [0.196, 0.274] & [0.0465, 0.742] & [0.208, 0.273] & [0.159, 0.245] & [0.0452, 0.725] & [0.101, 0.407] \\ [0.14, 0.276] & [0.0698, 0.968] & [0.138, 0.276] & [0.153, 0.279] & [0.0514, 0.644] & [0.0834, 0.371] \\ [0.137, 0.262] & [0.031, 0.839] & [0.131, 0.259] & [0.169, 0.232] & [0.0552, 0.828] & [0.0955, 0.417] \\ [0.16, 0.222] & [0.0388, 0.936] & [0.158, 0.237] & [0.161, 0.225] & [0.0481, 0.966] & [0.104, 0.338] \\ [0.158, 0.231] & [0.0543, 0.677] & [0.151, 0.228] & [0.172, 0.284] & [0.0574, 0.725] & [0.106, 0.456] \end{pmatrix}$$

Thus, according to the actual SLO interval value of candidate CSPs on QoS attributes, the trust level of cloud services of each candidate CSPs can be obtained by employing TAM. The specific process are described as follows.

First, the normalized decision matrix of candidate CSPs $\boldsymbol{R}$ can be constructed by the data of Table III and equations (8) - (10), as shown in Figure 3.

Second, the weight of each QoS attribute can be calculated by $\boldsymbol{R}$ and equations (11)-(16). The weight vector $\boldsymbol{\omega}$ of QoS attributes can be obtained, denoted as follows.

$$\boldsymbol{\omega} = \begin{pmatrix} 0.0295 & 0.118 & 0.150 & 0.167 & 0.247 & 0.288 \end{pmatrix}.$$

Third, the trust level of each candidate CSP can be calculated by aggregating $\boldsymbol{R}$ with $\boldsymbol{\omega}$.

$$z_1(\boldsymbol{\omega}) = [0.109, 0.474], z_2(\boldsymbol{\omega}) = [0.0953, 0.477],$$
$$z_3(\boldsymbol{\omega}) = [0.0968, 0.525], z_4(\boldsymbol{\omega}) = [0.102, 0.526],$$
$$z_5(\boldsymbol{\omega}) = [0.107, 0.473].$$

Then, the possibility degree matrix $\boldsymbol{P}$ of candidate CSPs can be constructed by equation (18) based on their trust level.

$$\boldsymbol{P} = \begin{pmatrix} 0.5 & 0.508 & 0.476 & 0.472 & 0.502 \\ 0.493 & 0.5 & 0.469 & 0.465 & 0.494 \\ 0.524 & 0.531 & 0.5 & 0.496 & 0.526 \\ 0.528 & 0.535 & 0.504 & 0.5 & 0.53 \\ 0.498 & 0.506 & 0.474 & 0.47 & 0.5 \end{pmatrix}$$

Finally, the ordering vector of $\boldsymbol{P}$ can be calculated by equation (19), represented as follows.
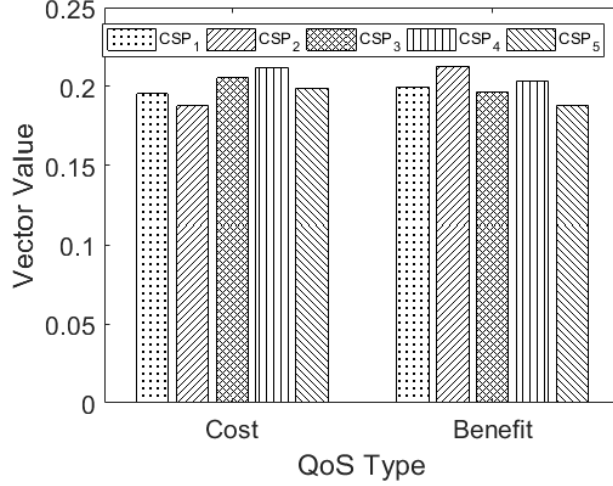
Figure 4: The priority ranking of candidate CSPs based on cost and benefit QoS.

$$\boldsymbol{v} = \begin{pmatrix} 0.198 & 0.196 & 0.204 & 0.205 & 0.197 \end{pmatrix}.$$

Therefore, the priority ranking of candidate CSPs can be obtained by sorting the components of $\boldsymbol{v}$. That is,

$$CSP_4 \underset{0.504}{\succ} CSP_3 \underset{0.524}{\succ} CSP_1 \underset{0.502}{\succ} CSP_5 \underset{0.506}{\succ} CSP_2.$$

It can seen that CSP_4 is the best and CSP_2 is the worst.

Similarly, the priority ranking of candidate CSPs can be obtained according to the different types of QoS attributes, as shown in Figure 4. As can be seen from Figure 4, the CSPs priority ranking obtained according to the benefit QoS is different from that obtained based on the cost QoS. For the cost QoS, the priority ranking of candidate CSPs is: $CSP_4 > CSP_3 > CSP_5 > CSP_1 > CSP_2$. For the benefit QoS, the priority ranking of candidate CSPs is: $CSP_2 > CSP_4 > CSP_1 > CSP_3 > CSP_5$.

5.3. Performance Analysis and Comparison

In this section, the time complexity of TAM is analysed and compared with the traditional analytic hierarchy (AHP)-based cloud service assessment or ranking methods.

5.3.1. Time complexity of TAM

TCSC performs a trust level assessment of TAM for the request of each PCC. The assessment method of TAM is divided into five steps, and the time complexity of each step is related to the number of CSPs and QoS attributes to be assessed. Algorithm 1 illustrates the process of TAM. Therefore, it is assumed that the number of CSPs is m and the number of QoS attributes is n. The time complexity of TAM is analysed step by step.

- **Step 1:** In this step, a decision matrix consisting of the actual SLO values of m CSPs on the n QoS attributes needs to be constructed and normalized. Since the n QoS attributes may belong to different types (i.e., benefit and cost), in the worst case, the elements r_{ik} in the decision matrix $\boldsymbol{R}_{m \times n}$ need to be normalized by equation (9) and (10). Thus, the time complexity of constructing the normalized decision matrix is: $O(2mn + 2mn) = O(4mn)$.

- **Step 2:** The weight vector $\boldsymbol{\omega}$ of QoS attributes can be determined in this step. Firstly, the total deviation $D_k(\boldsymbol{\omega})$ of each CSP from other CSPs on each QoS attribute of normalized decision matrix need to be calculated according to equation (12) and (13). Secondly, the $D_k(\boldsymbol{\omega})$ need to be maximized by equation (14). Finally, the weight $\boldsymbol{\omega}$ of each QoS attribute can be calculated and normalized by equation (15) and (16). Thus, the time complexity of determining the weight vector of QoS attributes is: $O(2m^2 n + 2n)$.

- **Step 3:** In this step, the trust level of each CSP $z_i(\boldsymbol{\omega})$ can be calculated by aggregating the normalized decision matrix $\boldsymbol{R}$ with the weight vector $\boldsymbol{\omega}$. That is, the integrated value of m CSPs on n QoS attributes can be

obtained by equation (17). Therefore, the time complexity of calculating the trust level of CSPs is: $O(mn)$.

- **Step 4:** The purpose of this step is to construct the possibility degree matrix of CSPs. The possibility degree p_{ie} of pairwise comparison between the ith CSP and eth CSP can be calculated by equation (18). The possibility degree matrix $\boldsymbol{P}_{I \times I}$ can be constructed on the basis of all p_{ie}. The time complexity of this step is: $O(4m^2)$.

- **Step 5:** In order to facilitate PCC to select the trustworthy cloud service, the candidate CSPs need to be ranked by the ordering vector of the possibility degree matrix in this step. The ordering vector $\boldsymbol{v}$ of $\boldsymbol{P}$ can be calculated according to equation (19). The priority of m CSPs whose cloud service conforms to the QoS attributes requirements of PCC can be obtained by the ordering vector $\boldsymbol{v}$. Therefore, The time complexity of this step is: $O(m^2 + m)$.

In conclusion, in the worst case, the time complexity of TAM is as follows: $O(4mn + 2m^2n + 2n + mn + m^2 + m) = O(2n + 1)m^2 + (5n + 1)m + 2n$.

5.3.2. Performance Comparison

A two-way ranking method based on analytic hierarchy process (AHP) for cloud service mapping (denote as TRSM) was proposed in literature [20]. TRSM divides the QoS requirements of CSCs into multiple criteria layers according to the standard AHP method. Each layer contains different sub-attributes to make it easier to calculate the weight of each attribute and aggregate them accordingly. At the same time, CSPs act as the solution layer where the service quality of their cloud services were assessed and ranked. For a given CSC, the time complexity of TRSM in the worst case are analysed in [20]. That is, $O\left(\sum_{l=1}^{L} \sum_{i=1}^{N_{n-1}} n_{li}^3 + m^3 N_l + m \sum_{l=1}^{L} N_l\right)$, where, m denotes the number of CSPs, L denotes the number of QoS attributes layers, N_L denotes the number of Qos attributes contained in each layer, n_{li} denotes the number of sub-attributes contained in the ith QoS attribute of the lth layer, which are contained in the

$l-1$th layer. In general, the time complexity of TRSM depends on the above four parameters (i.e., m, L, N_L and n_{li}). However, for the particular cloud services (e.g., with the same functionality and service mode), the hierarchy of their QoS attributes is fixed, then the parameters L and N_L are constant. Hence, the time complexity of TRSM is actually determined by the number of CSPs m and the number of QoS attributes n, which can be represented as $O(n^3 + m^3 n + mn)$.

In [15], a trust evaluation method based on the technique for order preference by similarity to an ideal solution (TOPSIS) and the AHP (denote as AHP-TOPSIS for short) is proposed to evaluate the trustworthiness of CSPs. The QoS attributes were divided into two layers, objective layer and attributes layer. The TOPSIS method acted as the main process to evaluate the trustworthiness of CSPs based on QoS attributes.The AHP method was used to determine the weights of QoS attributes in the main process. For the sake of illustration, the literature let the number of CSPs be m and the number of QoS attributes be n, and elaborated the evaluation procedure step by step. According to the step 3 and its sub-steps for the weights assignment of QoS attributes (i.e., AHP was adopted), the time complexity can be roughly calculated and denoted as $O(6n^2 + (m+4)n + 4m)$. According to the other steps for the trustworthiness evaluation of CSPs based on QoS (i.e., TOPSIS was adopted), the time complexity can be roughly calculated and denoted as $O(2n^2 + (m+1)n + m)$. Thus, in the worst case, the time complexity of AHP-TOPSIS is as follows: $O(6n^2 + (m+4)n + 4m + 2n^2 + (m+1)n + m) = O(8n^2 + (2m+5)n + 5m)$.

Normally, the largest order of magnitude of the polynomial $O(m, n)$ would be taken as its time complexity. In order to compare the time complexity of TAM, TRSM and AHP-TOPSIS, let m and n represent the number of CSPs and the number of QoS attributes respectively. We assume that for the given number of QoS attributes, namely n is constant, the time complexity of TAM, TRSM and AHP-TOPSIS are determined by the number of CSPs m and respectively denoted as $O(m^2)$, $O(m^3)$ and $O(m)$. Similarly, for the given number of CSPs m, namely m is constant, the time complexity of TAM and AHP-Ranking are determined by the number of QoS attributes n and respectively denoted as

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$O(n)$, $O(n^3)$ and $O(n^2)$.

It can be seen from the performance comparison that in the case of a constant number of CSPs, the proposed TAM outperforms TRSM and AHP-TOPSIS. In the case of a constant number of QoS attributes, the time complexity of TAM is betweent TRSM and AHP-TOPSIS. In order to verify the correctness of the analysis results, simulation experiment are carried out to illustrate the impact of the number of CSPs and the number of QoS attributes on the performance of the three methods.

5.3.3. Simulation Experiment

The simulation are performed on a DELL desktop computer with the following configuration: an Intel Core i5 2.7 GHz CPU, 8 GB RAM, and the Windows 10 operating system. It is assumed that the number of CSPs is m and the number of QoS attributes is n. The SLO of QoS attribute is set as a single value and randomly assigned in advance, so as to analyze the impact of the change of m and n on the performance of each evaluation method. The execution time in the following experiments are the mean value after repeated 10 times under the same conditions.

Condition 1: We set the number of CSPs as a constant, namely $m = 6$ and increase n from 50 to 500 with a step 50. The experimental result is shown in figure 5(a).

Condition 2: We set the number of QoS attributes as a constant, $n = 30$ and increase m from 6 to 60 with a step 6. The experimental result is shown in figure 5(b).

Figure 5(a) shows that the execution time of the three competitive methods increases with the number of QoS attributes in the case of the number of CSPs is constant, where TRSM has the largest increase amplitude. Figure 5(b) shows that the execution time of the three competitive methods increase with the number of CSPs in the case of the number of QoS attributes is constant, where TRSM increase the most, TAM followed, and AHP-TOPSIS increase the least.

The experimental results show that TRSM has the fastest growth rate in
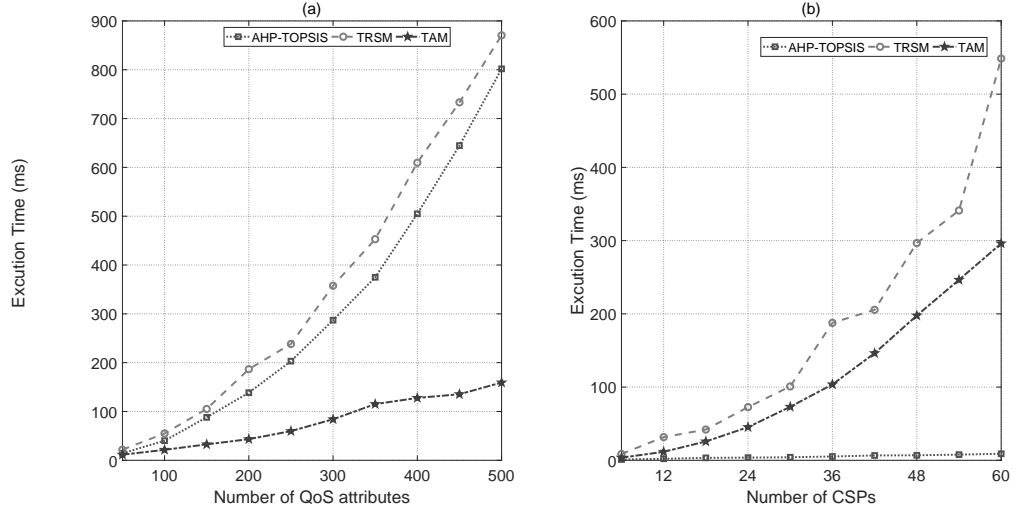
Figure 5: The performance comparision of the three competitive methods under two conditions.

execution time under two different conditions, while AHP-TOPSIS and TAM have their advantages and disadvantages respectively. This is because TRSM evaluates the priority of CSPs based on hierarchical QoS attributes. The priority of CSPs is calculated based on each QoS attribute of each layer. The value of different CSPs with respect to each QoS attribute in the upper layer can be obtained by aggregation. Then the above steps are repeated until the priority of CSPs at the highest QoS level is obtained, so the time execution of TRSM is the highest.

However, it is worth noting that TRSM and AHP-TOPSIS are applicable to the QoS attribute with single value, but they are not well applicable to the QoS attribute with interval value, and they both assign weights of QoS attributes based on subjective preference. TAM can handle the above problems well.

6. Conclusion

In this paper, we propose a assessment and selection framework for trustworthy cloud services, which facilitate PCCs to select a trustworthy cloud service

based on their actual QoS requirements. For the convenience of PCCs to select a trustworthy cloud service, a trust assessment component is designed in the framework to accept assessment requests initiated by PCCs and return assessment results to them. In order to accurately and efficiently assess the trust level of cloud services, a QoS-based trust model is proposed. This model represents a trust level assessment method based on the interval multiple attribute with a objective weight assignment method based on the deviation maximization to determine the trust level of cloud services provisioned by candidate CSPs. The advantage of proposed trust assessment method in time complexity is demonstrated by the process of performance analysis and comparison. The experimental result of a case study with an open source dataset show that the proposed trust model is effective in cloud service trust assessment and the help PCCs select a trustworthy CSP.

As future work, we aim to build a prototype for our proposed framework and implement the represented trust assessment model in a real cloud environment.

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