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Time-aware trustworthiness ranking prediction for cloud services using interval neutrosophic set and ELECTRE

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ABSTRACT

The imprecise quality of service (QoS) evaluations from consumers may lead to the inappropriate prediction for the trustworthiness of cloud services in an uncertain cloud environment. The service ranking prediction is a promising idea to overcome this deficiency of values prediction approaches by probing the ordering relations between cloud services concealed in the imprecise evaluations. To address the challenges for trustworthy service selection resulting from fluctuating QoS, flexible service pricing and complicated potential risks, this paper proposes a time-aware approach to predict the trustworthiness ranking of cloud services, with the tradeoffs between performance-cost and potential risks in multiple periods. In this approach, the interval neutrosophic set (INS) theory is utilized to describe and assess the performance-costs and potential risks of cloud services: (1) the original evaluation data about cloud services are preprocessed into the trustworthiness interval neutrosophic numbers (INNs); (2) the new INS operators are proposed with the theoretical proofs to calculate the possibility degree and the ranking values of trustworthiness INNs, contributing to the identification of the neighboring users based on the Kendall rank correlation coefficient (KRCC). The problem of time-aware trustworthiness ranking prediction is formulated as a multi-criterion decision-making (MCDM) problem of creating a ranked services list using INS, and an improved ELECTRE method is developed to solve it. The proposed approach is verified by experiments based on an appropriate baseline for comparative analysis. The experimental results demonstrate that the proposed approach can achieve a better prediction quality than the existing approach. The results also show that our approach works effectively in the risk-sensitive and performance-cost-sensitive application scenarios and prevent the malignant price competition launched by low-quality services.

1. Introduction

1.1. Motivation

Recently, with the proliferation of cloud services over the Internet, it has become more and more challenging to select the highly trustworthy services meeting the user-specific requirements from the abundant candidates [1,2]. Traditional service selection approaches employ the probability theory [3], fuzzy mathematics [4], rough set theory [5], interval number theory [6,7] and evidence theory [8] to predict the trustworthiness of cloud services based on the exact evaluation data from cloud service consumers. However, in an uncertain cloud environment, the real quality of service (QoS) of cloud services experienced by cloud service consumers is usually different from the QoS claimed by cloud service providers. The QoS evaluations from different consumers also show significant variations due to the various factors, such as different client features among users, unpredictable network congestions and unexpected exceptions [8,9]. Unfortunately, the imprecise QoS evaluation data has been a critical basis for decisions in order to accurately predict the trustworthiness of candidate services for the users. Inevitably, these evaluation data may lead to an inappropriate prediction result.

Currently, service ranking prediction becomes a promising idea to overcome the deficiency of the existing approaches based on the imprecise evaluation values [10,11]. Unlike the traditional value prediction approaches, the ranking prediction examines the order of services under consideration for a particular user. Suppose there

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are a set of three cloud services, on which two users have observed the trustworthiness values of {0.5, 0.7, 0.9} and {0.3, 0.5, 0.7}, respectively. The trustworthiness values on these services observed by the two users are clearly different; nevertheless, their rankings are very close as the services are ordered in the same way. Thus, analyzing the ordering relations between services concealed in the imprecise evaluation values facilitates to improve the accuracy of identifying similar users and predicting the trustworthiness of services for users. However, in an uncertain cloud environment, it is still a critical issue to utilize the trustworthiness ranking prediction approach to select the highly trustworthy service from abundant candidates meeting the user-specific requirements. This task includes the following challenges:

(1) The performance and price of cloud services are usually not identical in the different periods. The existing research [12,13] has revealed that the cloud services' performance has the apparent characteristic of the periodic variation. Cloud services perform the best in the idle hours, and their performance deteriorates during the busy hours. Thus, cloud service providers usually adopt the dynamic pricing strategies for balancing loads or improving the energy efficiency, such as offering a discount from 8 PM to 9 PM [13]. Service consumers can achieve a higher performance-cost of cloud services by changing the period of their usage, or enjoy a better performance in a specific period by paying more. It is helpful to select the trustworthy cloud services by considering the objective characteristics of periodic variation of their performance and price.
(2) Users have different preferences for the trustworthiness of cloud services in different periods. For many application domains, users' demands for computing systems are never stable. Even with the same computing infrastructures and software, at different time, Susers' demands might be different due to the constraints on performance, cost, and data quality [14]. For example, such demands are known in an interactive data analysis in the cloud [15] and data analytics of equipment operations in smart cities [16]. Thus, it is indispensable to support subjective user preferences for periods to predict the trustworthiness of cloud services.
(3) Recently, a series of cloud security events, occurred in Salesforce services, EC2 services, BPOS services, SONY Playstation services and iCloud services, have proven that cloud computing is fraught with potential risks that must be carefully evaluated prior to engagement [17,18]. Some organizations, including Cloud Security Alliance (CSA) [19], China Cloud Computing Promotion and Policy Forum (3CPP) [20], and researchers [21,22] have dedicated them to the risk assessment for a cloud. The primary potential risks to a cloud have been identified and analyzed [23,24]. Especially, recognized as important risks inherent to a cloud, the availability [25,26] of cloud services and the disruption or failure of cloud computing networks [27] are vulnerable to the heavy loads and networks' susceptibility in specified periods. In contrast to performance and costs of cloud services, these potential risks inherent to a cloud are more uncertain. The assessment of potential risks over multiple periods adds extra complexities to predict the trustworthiness values of cloud services.
(4) Users have different sensitivity to performance-cost and potential risks of cloud services in different application scenarios. For example, a stock exchange corporation, ready to purchase a cloud service to store massive amounts of stock trading data, must pay more attentions to the potential risks of this cloud storage service. However, a logistics company, preparing to purchase a cloud host service to deploy the express delivery query application not involving confidential data, may desire the performance-cost ratio of the service to be as high as possible due to the limited budget. In our previous research [12], we proposed the **c**loud service **i**nterval **n**eutrosophic **s**et (CINS) to support users' decision-making of service selection with the tradeoffs between performance-cost and potential risks. In CINS, the tradeoff coefficients represent both the importance of every period and the sensitive degrees to the performance-cost ratio, uncertainty and potential risks. Nevertheless, considering the complicated coupling relationships among the tradeoff coefficients, in practice, accurately determining the values of the tradeoff coefficients is a challenging task for the users without professional knowledge. The improper tradeoff coefficients do deteriorate the accuracy of prediction. Therefore, it is required to conveniently support users with the tradeoffs between performance-cost and potential risks in multiple periods.

1.2. Our contributions

To select the highly trustworthy cloud services from abundant candidates meeting user-specific requirements in an uncertain cloud environment, this paper formulates the problem of time-aware trustworthiness ranking prediction with the tradeoffs between performance-cost and potential risks in multiple periods as a multi-criterion decision-making (MCDM) problem. In this problem, every period is viewed as an evaluation criterion. The interval neutrosophic set (INS) theory is employed to measure the trustworthiness of cloud services by combining the objective characteristics of periodic variation of cloud services. Aiming at the complicated coupling relationship among the parameters, this paper redefines two mutually independent parameters consisting of the subjective period preferences and tradeoff coefficients. The new INS operators are proposed to calculate the possibility degree values and ranking values of trustworthiness interval neutrosophic numbers (INNs). These operators contribute significantly to the identification of neighboring users for a user by using the Kendall rank correlation coefficient (KRCC). Based on these preparations, an improved ELECTRE (elimination and choice expressing reality) method [28] supporting the INS operators is developed to solve the MCDM problem for achieving the trustworthiness ranking prediction of candidate services.

The main contributions of this paper are as follows:

(1) Aiming at the objective characteristics of periodic variation for cloud services, we utilize the INS theory to measure the trustworthiness values of cloud services and employ the mutually independent parameters to depict the subjective period preferences and tradeoff coefficients following the users' demands. To conveniently support the decision-making of trustworthy service selection with the tradeoffs between performance-cost and potential risks, we design new INS operators to calculate the possibility degree values and ranking values of trustworthiness INNs based on theoretical proofs.
(2) We employ the trustworthiness INNs to assess the performance–costs and potential risks of cloud services from the new perspective of time series analysis and then exploit the ordering relations between services to accurately identify similar users via the Kendall rank correlation coefficient. Based on the INS theory, we formulate the time-aware trustworthiness ranking prediction problem with the tradeoffs between performance-costs and potential risks over multiple periods as an MCDM problem. We then develop an

improved ELECTRE method supporting the INS operators to solve this problem.

(3) We examine the proposed approach through experiments on a real-world dataset and an appropriate baseline for our comparative analysis. The results demonstrate that the proposed approach can achieve a better prediction quality than the existing approach. The proposed approach can work effectively in the risk-sensitive application scenario and the performance-cost-sensitive application scenario, and also prevent malignant price competition launched by some low-quality services.

The rest of this paper is organized as follows. Section 2 introduces the related work. Section 3 provides the preliminary concepts. Section 4 defines the problem. Section 5 presents an identification method of neighboring users based on the KRCC. Section 6 puts forward the MCDM procedure of trustworthiness ranking prediction. Section 7 describes the experiments and analyzes the results. Finally, the conclusions and further study are given in Section 8.

2. Related work

2.1. Prediction methods for cloud services

In conventional studies, some theories and techniques, such as the probability theory, the fuzzy theory, the evidence theory, the social network analysis, the collaborative filtering and matrix factorization techniques, are employed to predict the QoS or trustworthiness of cloud services and assist users to select suitable services.

Mehdi et al. [3] presented a QoS-aware approach based on probabilistic models to aid service selection by allowing consumers to maintain a trust model of each service provider they have interacted with in the past. Peng et al. [29] proposed a QoS-driven service selection method for group users in which alternatives are ranked based on QoS and preferences of group members as described by fuzzy terms. Ma et al. [8] presented an evidence theory-based fusion approach to predicting the QoS of cloud services by filtering out the unreliable evaluations. Huang et al. [30] proposed a novel algorithm based on online user communities to estimate the QoS evaluations. Mo et al. [31] put forward a cloud-based mobile multimedia recommendation system in which the user contexts, user relationships, and user profiles are collected from video-sharing websites. Zheng et al. [32] employed the collaborative method to take advantage of past experiences from service consumers and designed a neighborhood-integrated approach for personalized web service QoS prediction.

For improving the accuracy of prediction, Hu et al. [33] proposed a time-aware collaborative filtering algorithm to predict the missing QoS values by calculating the similarities between services and users based on the historical data of services at different time intervals. Zhong et al. [34] proposed a time-aware service recommendation approach that extracts the time sequence of topic activities and the service-topic correlation from service usage history and then employs a time series prediction method to forecast topic evolution and future service activities. Based on the intuition that users inside a neighborhood are likely to share the similar services invocation experience, Yin et al. [35] proposed a collaborative matrix factorization framework to predict the personalized QoS values by leveraging the personal geographical and QoS information to identify the robust neighborhoods. Ding et al. [36] designed a framework for conducting cloud service trustworthiness evaluation by combining QoS prediction and customer satisfaction estimation.

The above prediction approaches might have the limitations due to the deficiency caused by the imprecise evaluation values. Thus, the service ranking prediction becomes a promising idea to enhance the accuracy of prediction. Zheng et al. [10] employed the KRCC to evaluate the user similarity by considering the number of inversions of service pairs and developed a QoS ranking prediction framework for personalized cloud services ranking. Mao et al. [11] utilized the KRCC-based method to measure the user similarity by combining the occurrence probability of relation pairs and adopted the Particle Swarm Optimization (PSO) algorithm to solve the QoS ranking prediction problem. However, the related work has not considered two factors, including the user preferences for different periods and the tradeoffs between performance-cost and potential risks in multiple periods, while the two factors could facilitate to improve the customer satisfaction indicated by the previous research [12].

2.2. MCDM methods for service selection

MCDM is concerned with structuring and solving decision problems involving multiple criteria. Typically, there is not a unique optimal solution for them, and it is necessary to use decision-maker's preferences to differentiate the candidate solutions. MCDM methods can be used to solve the service selection problem, provided that the trustworthiness attributes and candidate services are finite. Techniques such as the analytic hierarchy process (AHP), fuzzy analytic hierarchy process (FAHP), analytic network process (ANP), ELECTRE and TOPSIS fall into this category.

AHP, FAHP and ANP methods provide a comprehensive framework for structuring a complex decision problem and assist the decision makers to systematically evaluate a group of factors or criteria that relate to the goal of problem. To exactly assess the performance of candidate services, these methods are usually used to measure the weights of attributes of QoS or trustworthiness. For example, Godse et al. [37] presented an AHP-based SaaS service selection approach to scoring and ranking services. Garg et al. [38] employed AHP method to measure the attributes of QoS and rank cloud services. Menzel et al. [39] introduced ANP method for selecting IaaS services. Ma et al. [8] proposed a trustworthy cloud service selection approach that employs the FAHP method to calculate the weights of user features.

TOPSIS method can effectively assess the advantages and disadvantages of cloud services for service selection when the positive and negative ideal solutions in an n-dimensional space are available. For example, Sun et al. [40] presented a multi-criteria decision-making technique based on fuzzy TOPSIS method to rank cloud services. Nevertheless, in the time-aware trustworthiness ranking prediction problem, it is unpractical to identify the optimal or worst trustworthiness ranking list of candidate cloud services.

ELECTRE is an important outranking method of decision making and now has been applied to many fields, such as business management, energy management, information technology, financial management [28]. For example, Silas et al. [41] developed a cloud service selection middleware based on ELECTRE method. However, no literatures have studied the trustworthiness ranking prediction of cloud services by combining INS and ELECTRE method from the time series analysis.

2.3. Neutrosophic set theory and its applications

Since Zadeh presented the fuzzy set (FS) theory in 1965, many novel extensions have been proposed to settle the issues surrounding the imprecise, incomplete or uncertain information. These extensions include interval-valued fuzzy set (IVFS) [42], intuitionistic fuzzy sets (IFS) [43] and interval-valued intuitionistic fuzzy sets (IVIFS) [44]. Based on the fact that IFSs cannot handle indeterminate information [45], Smarandache [46] proposed the neutrosophic logic and the neutrosophic set (NS). An NS is a set of neutrosophic numbers (NNs) and an extension to IFS's standard interval [0, 1]. Each neutrosophic number (NN) possesses the degrees of truth, indeterminacy and falsity, whose values lie in the non-standard unit interval $]0^-, 1^+[$, and the degrees of truth, indeterminacy and falsity are independent. The uncertainty involved here, that is, the indeterminacy factor, is independent of truth and falsity values. NS has been used in a variety of fields, including intrusion detection systems [47], image segmentation [48,49], artificial intelligence [50], social network analysis [51] and financial data set detection [52].

For the convenience of application of NS in a practical application, Wang et al. [53] proposed an instance of NS called a single-valued neutrosophic set (SVNS). In turn, Ye [54] put forward a simplified neutrosophic set (SNS), which can be described by three real numbers in the real unit interval [0, 1]. Sometimes the degrees of truth, falsity and indeterminacy in a certain statement cannot be precisely defined in real situations, but they can be denoted by several possible interval values, requiring the interval neutrosophic set (INS). Wang et al. [53] proposed the concepts of INS and interval neutrosophic number (INN), and provided its set-theoretic operators.

NS has also been applied to MCDM problems. Ye [45] developed an MCDM approach by using SVNS correlation coefficient measurement. Zhang et al. [55] presented a new correlation coefficient measure of INS and developed an MCDM method that takes into account the influence of the evaluations' uncertainty and both the objective and subjective weights. In another study, Liu et al. [56] proposed several novel SVNS aggregation operators based on Hamacher operations and developed a multi-criteria group decision-making approach. To address the situations that the criteria are not independent and subject to compensation, Zhang et al. [57] put forward an outranking approach based on INS and ELECTRE IV for MCDM problems. Şahin et al. [58] proposed an MCDM method based on the inclusion measure for INS.

The above work focuses on the application of NS and INS in generalized MCDM problems based on theoretical analysis. To effectively address the specific problems, it is necessary to constantly develop the NS and INS theories for meeting the diverse users' requirements of decision-making in different application scenarios. In the previous research [12], we proposed the cloud service interval neutrosophic set (CINS) and the relevant operators to support the time-aware trustworthy cloud service selection. However, the CINS approach might lead to an unsatisfactory result when the proper tradeoff coefficients are unavailable. Moreover, the ordering relations between services have not been exploited to identify similar users for improving the accuracy of service selection.

To the best of our knowledge, no similar research has investigated the time-aware trustworthiness ranking prediction using the INS theory and ELECTRE method as what we do in this paper. In our work, the tradeoffs between performance-costs and potential risks in multiple periods are applied from the perspective of time series analysis.

3. Preliminary concepts

3.1. Trustworthiness of cloud services

According to the definition of trusted cloud services [59], a cloud service should be trustworthy if its behaviors and the corresponding consequences are consistent with the expectation of users. With our previous researches [12], the trustworthiness of a cloud service can be expressed with a 4-tuple as: $T = \langle F, C, R, U\rangle$.

(1) F represents the performance evaluation of the cloud service consisting of multiple attributes of QoS, such as response time, throughput, and so on; C represents the cost of the service. F and C jointly depict the behaviors and capacities of the cloud service.
(2) R and U represent the potential risks and uncertainty of the cloud service, respectively. R and U together describe the possibility of consequences inconsistent with the expectation of a user.

The cloud service consumers, cloud service providers and the third-party entities can provide the evaluation data about the performance, cost and potential risks of a cloud service. These evaluation data are the important evidences for accurately measuring the trustworthiness of the cloud service.

To compare and calculate the trustworthiness of candidate cloud services, we introduce the INS theory to define the trustworthiness of a cloud service as follows:

Definition 1. The trustworthiness of cloud service A is characterized by an INN $T_A = \langle O_A, U_A, R_A\rangle$. $O_A = [\inf O_A, \sup O_A]$ represents the evaluation interval value of the performance-cost ratio, equivalent to the truth-membership function of the INN. Especially, O_A directly represents the performance when all the candidate services are free or have the same prices. $R_A = [\inf R_A, \sup R_A]$ represents the evaluation interval value of the potential risks, equivalent to the falsity-membership function of the INN. $U_A = [\inf U_A, \sup U_A]$ represents the evaluation interval value of the uncertainty of O_A and R_A, equivalent to the indeterminacy-membership function of the INN. O_A, U_A, $R_A \in [0, 1]$, and $0 \le \sup O_A + \sup U_A + \sup R_A \le 3$.

A larger O_A with a smaller U_A and a smaller R_A yields a better evaluation on cloud service A. Thus, the comparison on the advantage and disadvantage of cloud services can be transformed into the comparison on the possibility degree of trustworthiness INNs. A formula is proposed to calculate the possibility degree of trustworthiness INNs as follows:

3.2. Possibility degree of trustworthiness INNs

Definition 2. Let two INNs $T_A = \langle[\inf O_A, \sup O_A], [\inf U_A, \sup U_A], [\inf R_A, \sup R_A]\rangle$ and $T_B = \langle[\inf O_B, \sup O_B], [\inf U_B, \sup U_B], [\inf R_B, \sup R_B]\rangle$, representing the trustworthiness values of cloud service A and B. The possibility degree of $T_A \ge T_B$ is defined by:

$$P(T_A \ge T_B) = \alpha \cdot P(O_A \ge O_B) + \beta \cdot P(U_B \ge U_A) + \gamma \cdot P(R_B \ge R_A), \tag{1}$$

where α, β and γ are the tradeoff coefficients representing the sensitive degree of the current user to performance-cost ratio, uncertainty and potential risks; $0 \le \alpha,\ \beta,\ \gamma \le 1$, and $\alpha + \beta + \gamma = 1$. The traditional method to calculate the possibility degree between two interval numbers $A = [\inf A, \sup A]$ and $B = [\inf B, \sup B]$ is as follows [60]:

$$P(A \ge B) = \frac{\min\left\{l^A + l^B, max\{\sup A - \inf B, 0\}\right\}}{l^A + l^B}, \tag{2}$$

where $l^A = \sup A - \inf A$, $l^B = \sup B - \inf B$. To achieve the more accurate calculation precision of possibility degree for interval numbers, we proposed a calculation method [7] to compute the values of $P(O_A \ge O_B)$, $P(U_B \ge U_A)$ and $P(R_B \ge R_A)$. For example, the possibility degree of $O_A \ge O_B$ is calculated by Eq. (3) when $\sup O_A \ge \sup O_B$:

$$P(O_A \ge O_B) = \begin{cases} 1, & \inf O_A \ge \sup O_B \\ 1 - \frac{(\sup O_B - \inf O_A)^2}{2 \times l^{O_A} \times l^{O_B}}, & \inf O_B \le \inf O_A \le \sup O_B \le \sup O_A, \\ \frac{2 \times \sup O_A - \sup O_B - \inf O_B}{2 \times l^{O_A}}, & \inf O_A \le \inf O_B \le \sup O_B \le \sup O_A \end{cases} \tag{3}$$

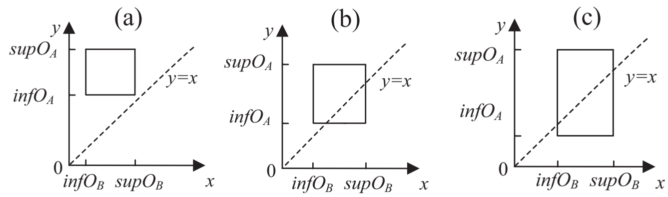

Fig. 1. Geometrical representation of possibility degree with (a) $\mathrm{inf}O_A \geq \mathrm{sup}O_B$; (b)$\mathrm{inf}O_B \leq \mathrm{inf}O_A \leq \mathrm{sup}O_B \leq \mathrm{sup}O_A$; (c) $\mathrm{inf}O_A \leq \mathrm{inf}O_B \leq \mathrm{sup}O_B \leq \mathrm{sup}O_A$.

where $l^{O_A} = \mathrm{sup}O_A - \mathrm{inf}O_A$ and $l^{O_B} = \mathrm{sup}O_B - \mathrm{inf}O_B$. Especially, $P(O_A \geq O_B) = 0.5$ when$O_A = O_B$, and $P(O_A \geq O_B) = 1 - P(O_B \geq O_A)$ when $\mathrm{sup}O_A < \mathrm{sup}O_B$.

A geometrical analysis method shown in Fig. 1 can deduce Eq. (3). In Fig. 1, O_A lies in the y axis and O_B lies in the x axis. The four points consisting of $\mathrm{inf}O_A$, $\mathrm{sup}O_A$, $\mathrm{inf}O_B$, and $\mathrm{sup}O_B$ compose a rectangle. There are six situations about the rectangle and the straight line $y = x$. According to the complementarity, we shall consider only three of them as shown in Fig. 1. The possibility degree of $O_A \geq O_B$ is the ratio of area above the straight line $y = x$ to the rectangular area, and Eq. (3) can easily be deduced.

Theorem 1. *According to Eq. (3), the following expressions are true.*

(T1a) $0 \leq P(O_A \geq O_B) \leq 1$.
(T1b) $P(O_A \geq O_B) = 1$ *when* $\inf O_A \geq \mathrm{sup}O_B$.
(T1c) $P(O_A \geq O_B) = 0$ *when* $\inf O_B \geq \mathrm{sup}O_A$.
(T1d) $P(O_A \geq O_A) = 0.5$.
(T1e) $P(O_A \geq O_B) + P(O_B \geq O_A) = 1$.

Proof. According to Fig. 1 and Eq. (3), $P(O_A \geq O_B)$ is just the ratio of area above the straight line $y = x$ to the rectangular area composed of $\mathrm{inf}O_A$, $\mathrm{sup}O_A$, $\mathrm{inf}O_B$, and $\mathrm{sup}O_B$. Obviously, (T1a), (T1b), (T1c), (T1d) and (T1e) are right. Thus, Theorem 1 holds.

Obviously, $P(U_B \geq U_A)$ and $P(R_B \geq R_A)$ can also be similarly calculated by Eq. (3) satisfying the Theorem 1.

Theorem 2. *According to Definition 2, the following expressions are true.*

(T2a) $0 \leq P(T_A \geq T_B) \leq 1$.
(T2b) $P(T_A \geq T_B) = 1$ *when* $\inf O_A \geq \mathrm{sup}O_B$, $\mathrm{inf}U_B \geq \mathrm{sup}U_A$ *and* $\inf R_B \geq \sup R_A$.
(T2c) $P(T_A \geq T_B) = 0$ *when* $\inf O_B \geq \mathrm{sup}O_A$, $\mathrm{inf}U_A \geq \mathrm{sup}U_B$ *and* $\inf R_A \geq \sup R_B$.
(T2d) $P(T_A \geq T_A) = 0.5$.
(T2e) $P(T_A \geq T_B) + P(T_B \geq T_A) = 1$.

Proof. (T2a) According to Theorem 1, $0 \leq P(O_A \geq O_B) \leq 1$, $0 \leq P(U_B \geq U_A) \leq 1$, $0 \leq P(R_B \geq R_A) \leq 1$. In addition, Eq. (1) satisfies $0 \leq \alpha,\ \beta,\ \gamma \leq 1$, and $\alpha + \beta + \gamma = 1$. Assuming that $P^M = \max\{P(O_A \geq O_B), P(U_B \geq U_A), P(R_B \geq R_A)\}$, then,

$$\begin{aligned} P(T_A \geq T_B) &= \alpha \cdot P(O_A \geq O_B) + \beta \cdot P(U_B \geq U_A) + \gamma \cdot P(R_B \geq R_A) \\ &\leq (\alpha + \beta + \gamma) \cdot P^M \leq P^M. \end{aligned}$$

Thus, $0 \leq P(T_A \geq T_B) \leq 1$.

(T2b) When $\inf O_A \geq \mathrm{sup}O_B$, then $P(O_A \geq O_B) = 1$. Similarly, when $\mathrm{inf}U_B \geq \mathrm{sup}U_A$, $P(U_B \geq U_A) = 1$; and when $\inf R_B \geq \sup R_A$, $P(R_B \geq R_A) = 1$. Then, when $\inf O_A \geq \mathrm{sup}O_B$, $\mathrm{inf}U_B \geq \mathrm{sup}U_A$, and $\inf R_B \geq \sup R_A$, we can deduce that

$$\begin{aligned} P(T_A \geq T_B) &= \alpha \cdot P(O_A \geq O_B) + \beta \cdot P(U_B \geq U_A) + \gamma \cdot P(R_B \geq R_A) \\ &= \alpha + \beta + \gamma = 1 . \end{aligned}$$

(T2c) When $\inf O_B \geq \mathrm{sup}O_A$, then $P(O_A \geq O_B) = 0$. Similarly, when $\mathrm{inf}U_A \geq \mathrm{sup}U_B$, $P(U_B \geq U_A) = 0$; and when $\inf R_A \geq \sup R_B$, $P(R_B \geq R_A) = 0$. Then, when $\inf O_B \geq \mathrm{sup}O_A$, $\mathrm{inf}U_A \geq \mathrm{sup}U_B$, and $\inf R_A \geq \sup R_B$, we can deduce that

$$P(T_A \geq T_B) = \alpha \cdot P(O_A \geq O_B) + \beta \cdot P(U_B \geq U_A) + \gamma \cdot P(R_B \geq R_A) = 0.$$

(T2d) According to Theorem 1, $P(O_A \geq O_A) = 0.5$, $P(U_A \geq U_A) = 0.5$, $P(R_A \geq R_A) = 0.5$. Then, $P(T_A \geq T_A) = \alpha \cdot P(O_A \geq O_A) + \beta \cdot P(U_A \geq U_A) + \gamma \cdot P(R_A \geq R_A) = (\alpha + \beta + \gamma) \times 0.5$=0.5.

(T2e) Based on Eq. (1), $P(T_A \geq T_B) = \alpha \cdot P(O_A \geq O_B) + \beta \cdot P(U_B \geq U_A) + \gamma \cdot P(R_B \geq R_A)$, and $P(T_B \geq T_A) = \alpha \cdot P(O_B \geq O_A) + \beta \cdot P(U_A \geq U_B) + \gamma \cdot P(R_A \geq R_B)$. Then,

$$\begin{aligned} &P(T_A \geq T_B) + P(T_B \geq T_A) \\ &\quad = \alpha \cdot (P(O_A \geq O_B) + P(O_B \geq O_A)) \\ &\qquad + \beta \cdot (P(U_B \geq U_A) + P(U_A \geq U_B)) \\ &\qquad + \gamma \cdot (P(R_B \geq R_A) + P(R_A \geq R_B)) \\ &\quad = \alpha + \beta + \gamma = 1. \end{aligned}$$

Thus, Theorem 2 holds.

Let $T_i = \langle [\mathrm{inf}O_i, \mathrm{sup}O_i], [\mathrm{inf}U_i, \mathrm{sup}U_i], [\mathrm{inf}R_i, \mathrm{sup}R_i] \rangle$ $(1 \leq i \leq N)$ be the trustworthiness values of N cloud services (denoted as s_1-s_N). The possibility degree $P(T_i \geq T_j)$ between any two INNs can be obtained by Eq. (1), denoted as $P_{i,j}$. Then, a possibility degree matrix related to INNs can be created as follows:

$$P = \begin{pmatrix} P_{1,1} & \cdots & P_{1,N} \\ \vdots & \ddots & \vdots \\ P_{N,1} & \cdots & P_{N,N} \end{pmatrix}. \tag{4}$$

To rank the N cloud services, we employ the following method to calculate the ranking values of trustworthiness INNs for cloud services.

3.3. Ranking values of trustworthiness INNs

According to Theorem 2, P is a fuzzy complementary judgment matrix. The sum of every row in P is obtained as follows:

$$P_i = \sum\nolimits_{j=1}^{N} P_{i,j}.$$

A fuzzy consistent complementary judgment matrix $\overline{P} = (\overline{P_{i,j}})_{N \times N}$ is computed by the mathematical transformations based on P as follows [61]:

$$\overline{P_{i,j}} = \frac{P_i - P_j}{2(N-1)} + 0.5. \tag{5}$$

Then, a ranking vector $R = (r_1, r_2, \ldots, r_N)$ is gained by the normalization method via $\overline{P}$.

Theorem 3. *The ranking value of INN* T_i *in a set of INNs can be normalized by*:

$$r_i = \frac{1}{N(N-1)} \left(\sum\nolimits_{j=1}^{N} P_{i,j} + \frac{N}{2} - 1 \right), \tag{6}$$

where N is the total number of INNs.

Proof. Firstly, $\overline{P}$ is a fuzzy complementary judgment matrix satisfying $\overline{P_{i,j}} + \overline{P_{j,i}} = 1$ and $\overline{P_{i,i}} = 0.5$. Then,

$$\begin{aligned} r_i &= \frac{\sum_{j=1}^{N} \overline{P_{i,j}}}{\sum_{i=1}^{N} \sum_{j=1}^{N} \overline{P_{i,j}}} = \frac{\sum_{j=1}^{N} \overline{P_{i,j}}}{\sum_{i=1}^{N} \sum_{j=1,\ j>i}^{N} \left(\overline{P_{i,j}} + \overline{P_{i,i}} \right) + N \times 0.5} \\ &= \frac{\sum_{j=1}^{N} \overline{P_{i,j}}}{\frac{(N^2-N)}{2} + \frac{N}{2}} = \frac{\sum_{j=1}^{N} \overline{P_{i,j}}}{\frac{N^2}{2}}. \end{aligned}$$

Then, according to Eq. (5), r_i can be transformed into:

$$r_i = \frac{\sum_{j=1}^{N} \left(\frac{P_i - P_j}{2(N-1)} + 0.5 \right)}{\frac{N^2}{2}} = \frac{\sum_{j=1}^{N} \left(\frac{P_i - P_j}{N-1} \right) + N}{N^2}$$

Table 1
Definitions of key symbols.

Symbol	Meaning
$U^{\mathrm{C}} = \{u_1, u_2, \ldots, u_X\}$	U^{C} is the set of candidate users; X is the number of candidate users
$U^{\mathrm{N}} = \{u_1^*, u_2^*, \ldots, u_K^*\}$	U^{N} is the set of neighboring users; K is the number of neighboring users
$S^{\mathrm{T}} = \{s_1, s_2, \ldots, s_n\}$	S^{T} is the set of training services; n is the number of training services
$S^{\mathrm{C}} = \{s_1, s_2, \ldots, s_N\}$	S^{C} is the set of candidate services; N is the number of candidate services
$S^{\mathrm{R}} = \{s_{r1}, s_{r2}, \ldots, s_{rN}\}$	The ranking list of N candidate cloud services
$T^{\mathrm{S}} = \{t_1, t_2, \ldots, t_Y\}$	T^{S} is the set of timeslots; Y is the number of timeslots
$P^{\mathrm{T}} = \{p_1, p_2, \ldots, p_Z\}$	P^{T} is the set of periods; Z is the number of periods
d	The density coefficient of periods
$W = \{w_1, w_2, \ldots, w_Z\}$	The period preferences reflecting the importance degree of every period
$D = \{\alpha, \beta, \gamma\}$	The tradeoff coefficients
δ^{th}	The threshold of user similarity
$W^{\mathrm{I}} = \{w_1^{\mathrm{I}}, w_2^{\mathrm{I}}, \ldots, w_H^{\mathrm{I}}\}$	W^{I} is the weights vector of evaluation indicators; H is the number of evaluation indicators
$o_{i,j}^k$	The original evaluation of the kth indicator of service #i in timeslot #j
$o_{i,j}^{k*}$	The predicted evaluation of the kth indicator of service #i in timeslot #j
$o_{i,j}^{k,m}$	The original evaluation of the kth indicator of service #i in timeslot #j provided by user #m
$T_{i,j}^k = < O_{i,j}^k, U_{i,j}^k, R_{i,j}^k >$	The trustworthiness INN of service #i in period #j related to user #k

$$= \frac{\sum_{j=1}^{N}\left(P_i - P_j\right) + N(N-1)}{N^2(N-1)}$$

$$= \frac{NP_i - \sum_{j=1}^{N}\left(P_j\right) + N(N-1)}{N^2(N-1)}$$

$$= \frac{P_i - \frac{\sum_{i=1}^{N}\sum_{j=1,j>i}^{N}\left(\overline{P_{i,j}} + \overline{P_{i,i}}\right) + N\times 0.5}{N} + (N-1)}{N(N-1)}$$

$$= \frac{P_i - \frac{N^2}{2N} + (N-1)}{N(N-1)} = \frac{\sum_{j=1}^{N} P_{i,j} + \frac{N}{2} - 1}{N(N-1)}.$$

Thus, Eq. (6) holds.

By sorting the ranking vector $R = (r_1, r_2, \ldots, r_N)$, a ranking list of the N cloud services can be obtained as follows: $s_{r1} \succ s_{r2} \succ \ldots \succ s_{rN}$, where s_{ri} represents the ith cloud service in the ranking list.

4. Modeling problem

In this section, we model the problem of time-aware trustworthiness ranking prediction and introduce the solving process. The definitions of some key symbols used in the following sections are shown in Table 1.

4.1. Problem definition

The problem of time-aware trustworthiness ranking prediction for cloud services with the tradeoffs between performance-cost and potential risks in multiple periods can be formulated as an MCDM problem, in which every period is viewed as an evaluation criterion. The problem model is shown in Fig. 2.

From Fig. 2, the input data of this problem consists of:

(1) The evaluation data about performance, costs and potential risks of cloud services: these data can be provided by cloud service consumers or relevant organizations, such as CSA and 3CPP. Considering that the direct evaluation data about the uncertainty of cloud services are usually unavailable in the real world, we will employ the cloud model theory to deduce the uncertainty of cloud services by measuring the dispersion of evaluations about performance, costs and potential risks.

(2) The period preferences: $W = \{w_1, w_2, \ldots, w_Z\}$, which reflects the importance degree of Z periods for the current user. $0 \le w_i \le 1$ and $\sum_{i=1}^{Z} w_i = 1$.

(3) The tradeoff coefficients: $D = \{\alpha, \beta, \gamma\}$, which reflects the sensitive degree to performance-cost and potential risks for the current users. $0 \le \alpha,\ \beta,\ \gamma \le 1$, and $\alpha + \beta + \gamma = 1$.

Assuming that $S^{\mathrm{T}} = \{s_1, s_2, \ldots, s_n\}$ is the set of training services that have been invoked by the current user and other service consumers; $S^{\mathrm{C}} = \{s_1, s_2, \ldots, s_N\}$ is the set of candidate services that meets the requirements of the current user; U^{C} is the set of candidate users who have invoked some services from S^{T}; U^{N} is the set of neighboring users who have a high similarity to the current user; $T^{\mathrm{S}} = \{t_1, t_2, \ldots, t_Y\}$ is the set of timeslots.

The core goal of this problem is to exactly predict the trustworthiness ranking of candidate services for the current user based on the historical evaluations. The output of this problem is a ranked list of the N candidate services: $s_{r1} \succ s_{r2} \succ \ldots \succ s_{rN}$.

The process of solving this problem can be generalized into seven steps as follows:

Step 1: Collect the original evaluation data of training services provided by candidate users from U^{C}, and preprocess them into the trustworthiness INNs matrix. In every period, a trustworthiness INN is used to objectively measure the performance-cost ratio, uncertainty and potential risks of a training service.

Step 2: Calculate the trustworthiness ranking of training services for every candidate user in U^{C}. Based on it, calculate the user similarity between the current user and other users by measuring the KRCC of training services in multiple periods.

Step 3: Select the top-K neighboring users for the current user in light of the specified similarity threshold. These neighboring users are aggregated into U^{N}.

Step 4: Collect the original evaluation data of candidate services provided by the neighboring users from U^{N}, and preprocess them into the trustworthiness INNs matrix for every candidate service from S^{C}.

Step 5: Establish the possibility degree matrix of trustworthiness INNs for candidate services in every period.

Step 6: Calculate the ranking value of every candidate cloud service in every period.

Step 7: Perform the improved ELECTRE operations based on the priority relation, relative priority, and inconsistency matrix, and then sort all the candidate services in accord with the net superiority value for every candidate service.

4.2. Preprocessing original data into trustworthiness INNs

The preprocessing method for transforming the original data into the trustworthiness INNs consists of six steps as follows:

Step 1: Collect the evaluation data about the performance, costs and potential risks of cloud services. The different types of cloud services have the different evaluation indicators of performance and potential risks. Taking the performance evaluation for exam-

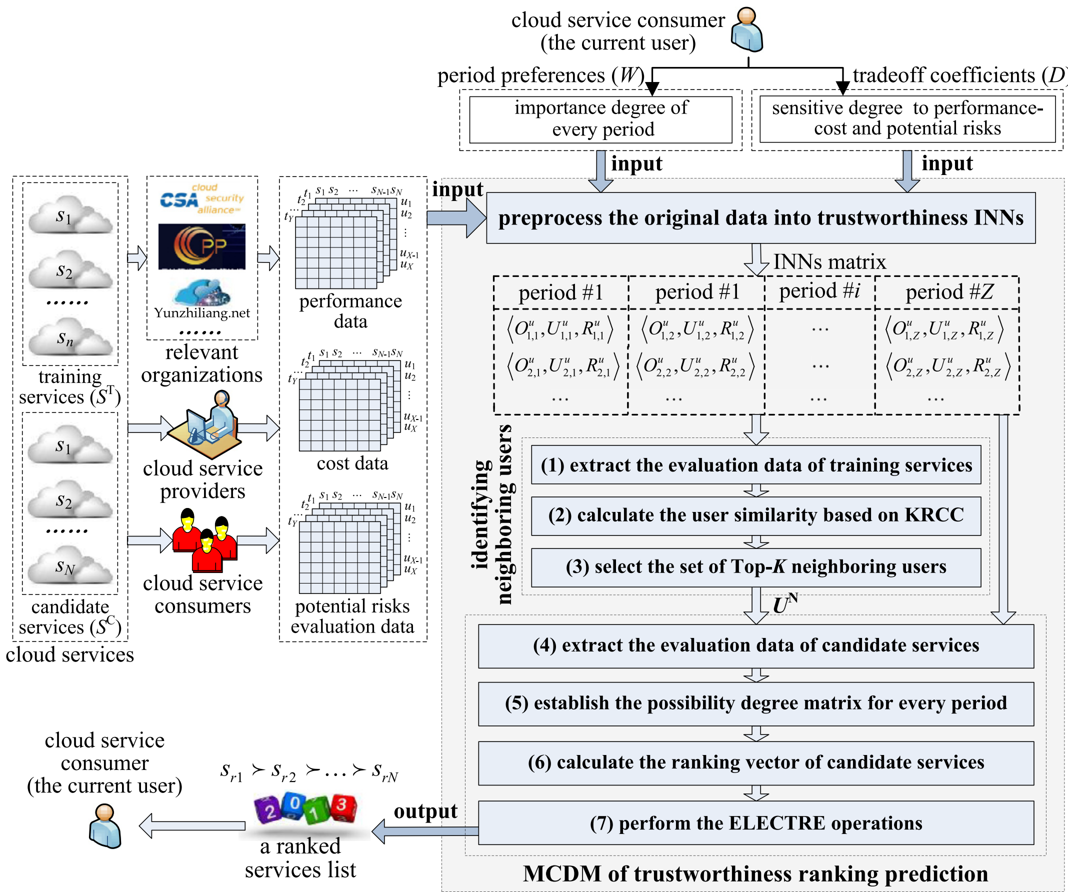

Fig. 2. Problem model.

ple, the original evaluation matrix of n cloud services related to user u can be represented by:

$$O(u) = \begin{bmatrix} (o_{1,1}^1, o_{1,1}^2, \cdots, o_{1,1}^H) & (o_{1,2}^1, o_{1,2}^2, \cdots, o_{1,2}^H) & \cdots & (o_{1,Y}^1, o_{1,Y}^2, \cdots, o_{1,Y}^H) \\ (o_{2,1}^1, o_{2,1}^2, \cdots, o_{2,1}^H) & (o_{2,2}^1, o_{2,2}^2, \cdots, o_{2,2}^H) & \cdots & (o_{2,Y}^1, o_{2,Y}^2, \cdots, o_{2,Y}^H) \\ \vdots & \vdots & \cdots & \vdots \\ (o_{n,1}^1, o_{n,1}^2, \cdots, o_{n,1}^H) & (o_{n,2}^1, o_{n,2}^2, \cdots, o_{n,2}^H) & \cdots & (o_{n,Y}^1, o_{n,Y}^2, \cdots, o_{n,Y}^H) \end{bmatrix}, \tag{7}$$

where $o_{i,j}^k$ represents the evaluation value of the kth performance indicator of service #i in timeslot #j; Y is the number of timeslots; H is the number of performance indicators. The multiple attributes evaluations of potential risks can also be defined similarly by Eq. (7).

Step 2: Aggregate the multi-dimensional performance evaluations and risk evaluations into the comprehensive evaluations with weighted arithmetic averaging operator. The gain-type indicators can be normalized by:

$$\widehat{o_{i,j}^k} = \left(o_{i,j}^k - \min_{i=1}^{n} o_{i,j}^k\right) \Big/ \left(\max_{i=1}^{n} o_{i,j}^k - \min_{i=1}^{n} o_{i,j}^k\right). \tag{8}$$

The loss-type indicators are normalized by:

$$\widehat{o_{i,j}^k} = \left(\max_{i=1}^{n} o_{i,j}^k - o_{i,j}^k\right) \Big/ \left(\max_{i=1}^{n} o_{i,j}^k - \min_{i=1}^{n} o_{i,j}^k\right). \tag{9}$$

Let $W^I = \{w_1^I, w_2^I, \ldots, w_H^I\}$ be the weights vector of evaluation indicators. w_i^I represents the weight of the ith indicator assigned by the current user. $0 \le w_i^I \le 1$ and $\sum_{i=1}^{H} w_i^I = 1$. The comprehensive performance evaluation of service #i in timeslot #j related to user u can be determined by:

$$e_{i,j}^F(u) = \sum_{k=1}^{H} \left(\widehat{o_{i,j}^k} \times w_k^I\right). \tag{10}$$

Similarly, the comprehensive potential risk evaluation of service #i related to user u can also be defined.

Step 3: Calculate the performance-cost ratio of cloud services in every timeslot. Let $e_{i,j}^C$ be the normalized cost of service #i in timeslot #j. Then, the performance-cost ratio is defined as $e_{i,j}^O = e_{i,j}^F / e_{i,j}^C$.

Step 4: Divide the timeslots into multiple periods by analyzing the user's time zone and application requirements. The set of periods is noted as: $P^T = \{p_1, p_2, \ldots, p_Z\}$, where Z is the number of periods. Let d be the density coefficient of periods, assuming that the number of timeslots is d in every period. Then $Y = Z \times d$. In practice, d may be a variable, because the size of period could be different according to the diverse requirements from users.

Step 5: Transform the single-value evaluation data from the same period into the interval numbers by utilizing cloud model theory. The cloud model [62,63] is a cognitive model realizing the bidirectional transformation between qualitative concept and quantitative data based on probability statistics and fuzzy set theory. It can effectively represent the fuzziness, randomness and uncertain concepts, and has been applied in many fields [63–65]. In this paper, we establish the cloud models for performance-costs and potential risks to identify their interval numbers in every period. Let $E^{\mathrm{O}}_{i,j}(u) = \left\{e^{\mathrm{O}}_{i,d\times(j-1)+1}, e^{\mathrm{O}}_{i,d\times(j-1)+2}, \ldots, e^{\mathrm{O}}_{i,d\times j}\right\}$ be the performance-cost ratio data of service #i in period #j related to user u. The data is viewed as cloud drops and sent into the reverse cloud generator (RCG). Then, the cloud model of performance-cost of service #i in period #j can be obtained by:

$$\begin{cases} Ex^{\mathrm{O}}_{i,j} = \frac{1}{d} \times \sum_{k=1}^{d} e^{\mathrm{O}}_{i,d\times(k-1)+k} \\ En^{\mathrm{O}}_{i,j} = \sqrt{\frac{\pi}{2}} \times \frac{1}{d} \sum_{k=1}^{d} \left| e^{\mathrm{O}}_{i,d\times(k-1)+k} - Ex^{\mathrm{O}}_{i,j} \right| \\ HE^{\mathrm{O}}_{i,j} = \sqrt{\left| \frac{1}{d-1} \sum_{k=1}^{d} \left(e^{\mathrm{O}}_{i,d\times(k-1)+k} - Ex^{\mathrm{O}}_{i,j} \right)^2 - \left(En^{\mathrm{O}}_{i,j} \right)^2 \right|} \end{cases} \tag{11}$$

The performance-cost ratio of service #i in period #j relevant to user u is defined as $o_{i,j}$, described with an interval number as $o_{i,j} = \left[o^{\mathrm{L}}_{i,j}, o^{\mathrm{U}}_{i,j}\right]$. $o^{\mathrm{L}}_{i,j}$ and $o^{\mathrm{U}}_{i,j}$ are calculated by:

$$\begin{cases} o^{\mathrm{U}}_{i,j} = Ex^{\mathrm{O}}_{i,j} + En^{\mathrm{O}}_{i,j} + HE^{\mathrm{O}}_{i,j} \times \tau \\ o^{\mathrm{L}}_{i,j} = Ex^{\mathrm{O}}_{i,j} - En^{\mathrm{O}}_{i,j} - HE^{\mathrm{O}}_{i,j} \times \tau \end{cases}, \tag{12}$$

where τ is the influence coefficient of HE, suggested to remain in the interval range [0.1, 0.2] [7]. Similarly, the cloud model for potential risks also can be established, and the potential risks interval number of service #i in period #j is defined as $r_{i,j} = \left[r^{\mathrm{L}}_{i,j}, r^{\mathrm{U}}_{i,j}\right]$.

Step 6: Calculate the uncertainty interval of service #i in period #j. Let $\lambda^{\mathrm{O}}_{i,j} = \sqrt{\left(En^{\mathrm{O}}_{i,j}\right)^2 + \left(HE^{\mathrm{O}}_{i,j}\right)^2}$ and $\lambda^{\mathrm{R}}_{i,j} = \sqrt{\left(En^{\mathrm{R}}_{i,j}\right)^2 + \left(HE^{\mathrm{R}}_{i,j}\right)^2}$ be the uncertainty of performance-cost ratio and the uncertainty of potential risks of service #i in period #j, respectively. Then, the uncertainty interval number of service #i in period #j is defined by:

$$U_{i,j} = \left[u^{\mathrm{L}}_{i,j}, u^{\mathrm{U}}_{i,j}\right] = \left[\min\left\{\lambda^{\mathrm{O}}_{i,j}, \lambda^{\mathrm{R}}_{i,j}\right\}, \max\left\{\lambda^{\mathrm{O}}_{i,j}, \lambda^{\mathrm{R}}_{i,j}\right\}\right]. \tag{13}$$

Then, the original data of n cloud services related to user u is transformed into the trustworthiness INNs matrix as follows:

$$T^u = \begin{pmatrix} T^u_1 \\ T^u_2 \\ \vdots \\ T^u_n \end{pmatrix} = \begin{pmatrix} T^u_{1,1} & T^u_{1,2} & \cdots & T^u_{1,Z} \\ T^u_{2,1} & T^u_{2,2} & \cdots & T^u_{2,Z} \\ \vdots & \vdots & \vdots & \vdots \\ T^u_{n,1} & T^u_{n,2} & \cdots & T^u_{n,Z} \end{pmatrix}$$
$$= \begin{pmatrix} \left\langle O^u_{1,1}, U^u_{1,1}, R^u_{1,1} \right\rangle & \cdots & \left\langle O^u_{1,Z}, U^u_{1,Z}, R^u_{1,Z} \right\rangle \\ \vdots & \ddots & \vdots \\ \left\langle O^u_{n,1}, U^u_{n,1}, R^u_{n,1} \right\rangle & \cdots & \left\langle O^u_{n,Z}, U^u_{n,Z}, R^u_{n,Z} \right\rangle \end{pmatrix},$$

where $T^u_{i,j} = \left\langle O^u_{i,j}, U^u_{i,j}, R^u_{i,j} \right\rangle = \left\langle [o^{\mathrm{L}}_{i,j}, o^{\mathrm{U}}_{i,j}], [u^{\mathrm{L}}_{i,j}, u^{\mathrm{U}}_{i,j}], [r^{\mathrm{L}}_{i,j}, r^{\mathrm{U}}_{i,j}] \right\rangle$ is the trustworthiness INN of service #i in period #j related to user u.

In the following sections, we will discuss the identification method of neighboring users based on the KRCC and the MCDM procedure of the trustworthiness ranking prediction based on an improved ELECTRE method.

5. Identification method of neighboring users based on the KRCC

The neighboring users can be identified for the current user based on the KRCC, consisting of six steps as follows:

Step 1: Calculate the trustworthiness INNs of n training services. Collect the training data from candidate users who have invoked these services. Employ the preprocessing method to calculate the trustworthiness INNs of n training services for the candidate users and the current user. The trustworthiness INN of the ith training service in period #j related to the kth candidate user can be described by:

$$\begin{aligned} T^k_{i,j} &= \left\langle O^k_{i,j}, U^k_{i,j}, R^k_{i,j} \right\rangle \\ &= \left\langle \left[\mathrm{inf}O^k_{i,j}, \mathrm{sup}O^k_{i,j}\right], \left[\mathrm{inf}U^k_{i,j}, \mathrm{sup}U^k_{i,j}\right], \left[\mathrm{inf}R^k_{i,j}, \mathrm{sup}R^k_{i,j}\right] \right\rangle. \end{aligned} \tag{14}$$

Then, the comprehensive trustworthiness evaluation matrix of the kth candidate user in Z periods is obtained as follows:

$$T^k = \begin{pmatrix} T^k_{1,1} & \cdots & T^k_{1,Z} \\ \vdots & \ddots & \vdots \\ T^k_{n,1} & \cdots & T^k_{n,Z} \end{pmatrix}$$
$$= \begin{pmatrix} \left\langle O^k_{1,1}, U^k_{1,1}, R^k_{1,1} \right\rangle & \cdots & \left\langle O^k_{1,Z}, U^k_{1,Z}, R^k_{1,Z} \right\rangle \\ \vdots & \ddots & \vdots \\ \left\langle O^k_{n,1}, U^k_{n,1}, R^k_{n,1} \right\rangle & \cdots & \left\langle O^k_{n,Z}, U^k_{n,Z}, R^k_{n,Z} \right\rangle \end{pmatrix}.$$

Similarly, obtain the comprehensive trustworthiness INNs matrix of the current user, denoted as T^{o}.

Step 2: Establish the possibility degree matrix of every period for the current user and every candidate user by Eqs. (1) and (3). The possibility degree matrix of the kth candidate user in period #i can be gained as follows:

$$P^{k,i} = \begin{pmatrix} P^{k,i}_{1,1} & P^{k,i}_{1,2} & \cdots & P^{k,i}_{1,n} \\ P^{k,i}_{2,1} & P^{k,i}_{2,2} & \cdots & P^{k,i}_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ P^{k,i}_{n,1} & P^{k,i}_{n,2} & \cdots & P^{k,i}_{n,n} \end{pmatrix} = \begin{pmatrix} 0.5 & P^{k,i}_{1,2} & \cdots & P^{k,i}_{1,n} \\ P^{k,i}_{2,1} & 0.5 & \cdots & P^{k,i}_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ P^{k,i}_{n,1} & P^{k,i}_{n,2} & \cdots & 0.5 \end{pmatrix}.$$

Step 3: Calculate the ranking values of every training service by Eq. (6). The ranking matrix of the kth candidate user in Z periods can be obtained by:

$$R^k = \left(R^k_1,\ R^k_2,\ \ldots,\ R^k_Z\right) = \begin{pmatrix} r^k_{1,1} & \cdots & r^k_{1,Z} \\ \vdots & \ddots & \vdots \\ r^k_{n,1} & \cdots & r^k_{n,Z} \end{pmatrix}, \tag{15}$$

where R^k_i represents the ranking vector of the n training services in period #i related to the kth candidate user. Similarly, calculate the ranking vector of the n training services in period #i related to the current user, namely, R^{o}_i.

Step 4: Calculate the ranking similarity in every period between the current user and every candidate user. The existing researches employ the KRCC to evaluate the similarity between two rankings on the same set of services by considering the number of inversions of service pairs. The KRCC similarity between user u and user v is calculated by:

$$Sim(u, v) = \frac{C - B}{n(n-1)/2}, \tag{16}$$

where n is the number of training services; C is the number of concordant pairs between two lists; B is the number of discordant pairs. There are totally $n(n-1)/2$ pairs for n training services, and $C = n(n-1)/2 - B$. Thus, Eq. (16) is equal to

$$Sim(u, v) = 1 - \frac{4B}{n(n-1)}. \tag{17}$$

Based on Eq. (15), employ the KRCC to calculate the ranking similarity in period #m between the kth candidate user and the current user by:

$$\begin{aligned} Sim^k_m &= Sim\left(R^k_m, R^{\mathrm{o}}_m\right) \\ &= 1 - \frac{4 \times \sum_{i=1}^{n} \sum_{j=i+1}^{n} f\left(\left(r^k_{i,m} - r^k_{j,m}\right) \times \left(r^{\mathrm{o}}_{i,m} - r^{\mathrm{o}}_{j,m}\right)\right)}{n(n-1)}. \end{aligned} \tag{18}$$

where $f(x)$ is an indicator function and defined by:

$$f(x) = \begin{cases} 1, & \text{if } x < 0 \\ 0, & \text{otherwise} \end{cases}. \tag{19}$$

The value of $Sim(R_n^k, R_n^o)$ is within the interval of $[-1, 1]$, where 1 is obtained when the order of R_n^k is equal to the order of R_n^o, and -1 is obtained when the order of R_n^k is the exact reverse of the order of R_n^o;

Step 5: Calculate the comprehensive ranking similarity between the current user and every candidate user. Let $Sim^k = (Sim_1^k, Sim_2^k, \ldots, Sim_Z^k)$ be the ranking similarity vector of the kth candidate user, and $W = \{w_1, w_2, \ldots, w_Z\}$ be the period preference of the current user. W reflects the importance degree of every period. The comprehensive ranking similarity between the current user and the kth candidate user can be obtained by:

$$\delta_k = \sum_{i=1}^{Z} Sim_i^k \times w_i. \tag{20}$$

Step 6: Select the set of the top-K neighboring users for the current user. The users with the low similarities will be filtered out and the neighboring users are identified for the current user by:

$$U^{\mathrm{N}} = \left\{ u_i \middle| u_i \in U^{\mathrm{C}} \; \&\& \; \delta_i \geq \delta^{\mathrm{th}} \right\}, \tag{21}$$

where δ^{th} is the threshold ensuring the dissimilar users are filtered out. Let $U^{\mathrm{N}} = \{u_1^*, u_2^*, \ldots, u_K^*\}$ be the set of the top-K neighboring users, and K be the number of neighboring users.

6. MCDM procedure of trustworthiness ranking prediction based on an improved ELECTRE method

Assume that there are N candidate services, denoted as s_1–s_N. To solve the problem of trustworthiness ranking prediction of N candidate services with the tradeoffs between performance-cost and potential risks in multiple periods, the MCDM procedure based on an improved ELECTRE method is developed as follows:

(1) Collect the evaluation data of the candidate services provided by neighboring users. Taking the performance for example, the evaluation of the kth performance indicator of the ith candidate service in timeslot #j can be predicted by aggregating historical data from neighboring users with similarity weights as follows:

$$o_{i,j}^{k*} = \sum_{m=1}^{K} \left(o_{i,j}^{k,m} \times \delta_m \right) \Big/ \sum_{m=1}^{K} \delta_m,$$

where $o_{i,j}^{k,m}$ represents the evaluation value of the kth performance indicator of the ith candidate service in timeslot #j provided by user #m from U^{N}.

(2) Employ the preprocessing method to transform them into trustworthiness INNs. Then, a trustworthiness matrix of N candidate services in Z periods is denoted as follows:

$$T = \begin{pmatrix} T_1 \\ \vdots \\ T_N \end{pmatrix} = \begin{pmatrix} T_{1,1} & \cdots & T_{1,Z} \\ \vdots & \ddots & \vdots \\ T_{N,1} & \cdots & T_{N,Z} \end{pmatrix}.$$

(3) Establish the possibility degree matrix for every period by Eqs. (1) and (3). The possibility degree matrix of the kth period is denoted as follows:

$$P^k = \begin{pmatrix} P_{1,1}^k & P_{1,2}^k & \cdots & P_{1,N}^k \\ P_{2,1}^k & P_{2,2}^k & \cdots & P_{2,N}^k \\ \vdots & \vdots & \vdots & \vdots \\ P_{N,1}^k & P_{N,2}^k & \cdots & P_{N,N}^k \end{pmatrix} = \begin{pmatrix} 0.5 & P_{1,2}^k & \cdots & P_{1,N}^k \\ P_{2,1}^k & 0.5 & \cdots & P_{2,N}^k \\ \vdots & \vdots & \vdots & \vdots \\ P_{N,1}^k & P_{N,2}^k & \cdots & 0.5 \end{pmatrix},$$

where P^k is a complementary judgment matrix, and each element in this matrix $P_{i,j}^k$ denotes the possibility degree that the value of the ith candidate service exceeds that of the jth candidate service in period #k.

(4) Employ Eq. (6) to calculate the ranking vector of N candidate service in period #k based on P^k, denoted as $R_k = (r_{1,k}, r_{2,k}, \ldots, r_{N,k})^{\mathrm{T}}$, where $r_{i,k}$ represents the ranking value of the ith candidate service in period #k. Then, the comprehensive decision matrix consisting of the ranking vectors of candidate services in Z periods is denoted as follows:

$$R = (R_1 \; R_2 \; \ldots \; R_Z) = \begin{pmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,Z} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,Z} \\ \vdots & \vdots & \vdots & \vdots \\ r_{N,1} & r_{N,2} & \cdots & r_{N,Z} \end{pmatrix}.$$

(5) Calculate the normalized matrix of R by:

$$r_{i,j}^* = r_{i,j} \Big/ \sqrt{\sum_{i=1}^{N} r_{i,j}^2}. \tag{22}$$

Then, the normalized matrix is denoted as $R^* = (r_{i,j}^*)_{N\times Z}$.

(6) Identify the priority relation between two candidate services in every period based on R^*. The priority relation is defined according to the following rules: service #i is equivalent to service #j in period #k when $r_{i,k}^* = r_{j,k}^*$; service #i is superior to service #j in period #k when $r_{i,k}^* > r_{j,k}^*$; service #i is inferior to service #j in period #k when $r_{i,k}^* < r_{j,k}^*$. The consistency set is defined by:

$$J(i,j) = \left\{ k \middle| 1 \leq k \leq Z, \forall k, r_{i,k}^* \geq r_{j,k}^* \right\}, \tag{23}$$

where $J(i, j)$ represents the set of some periods in which service #i is superior or equivalent to service #j.

The inconsistency set is defined by:

$$J^-(i,j) = \left\{ k \middle| 1 \leq k \leq Z, \forall k, r_{i,k}^* < r_{j,k}^* \right\}, \tag{24}$$

where $J^-(i, j)$ is the set of some periods in which service #i is inferior to service #j.

(7) Compute the relative priority weights matrix by:

$$C^{\mathrm{R}} = \begin{pmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,Z} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,Z} \\ \vdots & \vdots & \vdots & \vdots \\ c_{N,1} & c_{N,2} & \cdots & c_{N,Z} \end{pmatrix}, \; c_{i,j} = \frac{\sum\limits_{k\in J(i,j)} w_k}{\sum_{k=1}^{Z} w_k}. \tag{25}$$

(8) Calculate the inconsistency matrix by:

$$D^{\mathrm{I}} = \begin{pmatrix} d_{1,1} & d_{1,2} & \cdots & d_{1,Z} \\ d_{2,1} & d_{2,2} & \cdots & d_{2,Z} \\ \vdots & \vdots & \vdots & \vdots \\ d_{N,1} & d_{N,2} & \cdots & d_{N,Z} \end{pmatrix}, \; d_{i,j} = \begin{cases} \dfrac{\max\limits_{k\in J^-(i,j)} \left\{ \left| w_k \times \left(r_{j,k}^* - r_{i,k}^* \right) \right| \right\}}{\max\limits_{k\in J^-(i,j)+J(i,j)} \left\{ \left| w_k \times \left(r_{j,k}^* - r_{i,k}^* \right) \right| \right\}}, & i \neq j \\ 0, & i = j \end{cases}. \tag{26}$$

For the candidate services #i and #j, a larger $c_{i,j}$ means a better candidate service #i, while a smaller $d_{i,j}$ means a better candidate service #i. Thus, the inconsistency matrix should be amended to ensure that it is similar to the consistency matrix.

(9) Compute the modification factor for the inconsistency matrix by:

$$e_{i,j} = c_{i,j} \times \left(1 - d_{i,j} \right). \tag{27}$$

Then, the modified weighting matrix is denoted as $E^{\mathrm{I}} = (e_{i,j})_{N\times Z}$.

Table 2
Range of timeslots and line number ranges for every period in the dataset.

Period	p_1	p_2	p_3	p_4	p_5	p_6
Range of timeslot	[0,10]	[11,20]	[21,30]	[31,40]	[41,51]	[52,63]
Line number range	[1,1139]	[1140,2146]	[2147,3135]	[3136,4105]	[4106,5159]	[5160,6294]

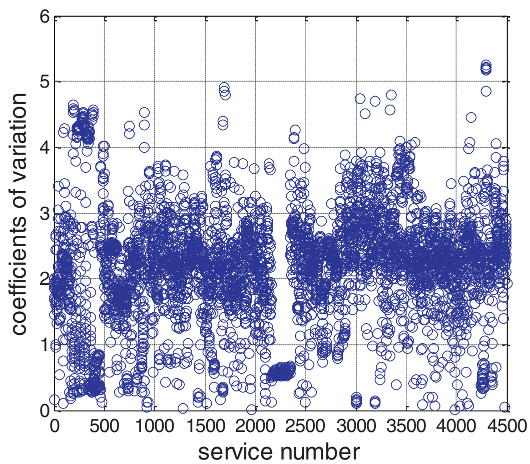

Fig. 3. Coefficients of variation of response time.

(10) Calculate the net superiority value for every candidate service by:

$$\xi_i = \sum_{j=1, j\neq i}^{N} e_{i,j} - \sum_{j=1, j\neq i}^{N} e_{j,i}, \quad i = 1, 2, \dots, N. \tag{28}$$

(11) Sort all the candidate services in light of the net superiority value ξ_i. A larger ξ_i means a better candidate service #*i*. According to ξ_i, the ranking list of candidate services can be obtained as follows: $s_{r1} \succ s_{r2} \succ \dots \succ s_{rN}$, where s_{ri} denotes the service with the net superiority value is at the *i*th number in the ranking.

7. Experiments

7.1. Experiment setup

To demonstrate our approach in experiments, we used WS-DREAM dataset #2 [66], which collected the real-world QoS evaluations from 142 users on 4500 services in 64 timeslots. The dataset has been applied into the researches concerned with cloud computing [12,67,68]. We analyzed the response time data of the dataset and found that these data has great dispersion due to the uncertain cloud environment. The coefficients of variation of response times of 3873 services were larger than 1.0, as shown in Fig. 3.

In the following experiments, let us consider a list of $n = 5$ training services and a list of $N = 8$ candidate services. The original data is divided into six periods. Table 2 shows the range of timeslots and the line number ranges for every period.

In the experiments, user #9 is viewed as the current user. The history evaluations from services #736–#740 are used as the training data to identify neighboring users for the current user in light of the period preferences and tradeoff coefficients. Taking services #741–#748 as candidate services, for example, we employ the original evaluations of response time in three numerical examples to demonstrate the proposed approach. The first example is for a risk-sensitive application scenario; the second one is for a performance-cost-sensitive application scenario; and the third one is for a low price competition application scenario. The original data used in the experiments is provided online [69].

Aiming at the response time, we assess the potential risks of services experienced by user #*i* in timeslot #*j* as follows:

$$v_{i,j} = \begin{cases} 0, & rt_{i,j} < \zeta \\ \left(\delta \times \left(rt_{i,j} - \zeta\right)\right)/\zeta, & \zeta \le rt_{i,j} \le (\zeta \times (1+\delta))/\delta, \\ 1, & (\zeta \times (1+\delta))/\delta < rt_{i,j} \end{cases} \tag{29}$$

where ζ is the user's expectation of response time and $rt_{i,j}$ represents the response time value experienced by user #*i* in timeslot #*j*. If $rt_{i,j} \le \zeta$, the *i*th user considers this service to be risk-free. δ is an adjustment factor that determinates the tolerable range for response time. In the experiments, we set $\zeta = 2$ s, $\delta = 0.25$, and $\tau = 0.1$ [12].

Considering that there is no cost data of services in the dataset, we assume that the costs of all the services are identical. In the MCDM procedure, the costs of services play a part with the performance of services together, namely performance-cost. The dataset demonstrates that the performance data of services is diverse enough to ensure the effectiveness of our outcome. In addition, we assume that service #745 attempts to improve its performance-cost ratio by offering different price discounts in the third example.

7.2. Metric of prediction results

To measure the accuracy of our approach, the real response time experienced by the current user is employed as an appropriate baseline for comparative analysis. The baseline sort value of service s_i $(i = 1, 2, \dots, N)$, noted as f_i^b, is calculated by:

$$f_i^b = \frac{\gamma \cdot \left|risk_i^b - risk^{b-}\right|}{\alpha \cdot \left|perf_i^b - perf^{b+}\right| + \gamma \cdot \left|risk_i^b - risk^{b-}\right|}, \tag{30}$$

where $perf_i^b = \sum_{j=1}^{Z} (w_j \times \sum_{k=(j-1)\times d+1}^{j\times d} perf_k)$ and $risk_i^b = \sum_{j=1}^{Z} (w_j \times \sum_{k=(j-1)\times d+1}^{j\times d} risk_k)$ represent the total response time and the total risk evaluation of s_i aggregated with weights of periods, respectively, and d is the density coefficient of periods; α and γ are the tradeoff coefficients; $perf_k$ and $risk_k$ represent the actual response time and risk value experienced by the current user in timeslot #*k*, respectively; $risk^{b-} = \max_{i=1}^{Z}\{risk_i^b\}$, representing the maximum of risk evaluations; $perf^{b+} = \max_{i=1}^{Z}\{perf_i^b\}$, representing the minimum of response time. The order of s_i in the baseline ranking can be obtained in accordance with f_i^b. The service with a large f^b ranks higher than the one with a small f^b.

The ranking prediction result of candidate services should be instructive to the current user for selecting the highly trustworthy services. Obviously, the current user usually pays the special attentions to the excellent candidates. Therefore, the rankings for the front part of the candidate services list are usually more important than those at the rear [11,70]. However, the original KRCC's measurement cannot ensure this, as it treats services at any position in the sequence equally. For example, assume that {3, 1, 2, 5, 4, 6} is the baseline ranking. There are two predicted rankings, {1, 2, 3, 5, 4, 6} and {3, 1, 2, 4, 6, 5}. The two predicted rankings obtain the same KRCC value, 0.7333. However, the second prediction result is actually better than the first one.

Table 3
Period preferences and tradeoff coefficients in Example 1.

W						D		
w_1	w_2	w_3	w_4	w_5	w_6	α	β	γ
0	0.15	0.35	0.35	0.15	0	0.35	0.10	0.55

Aiming at the limitation of the KRCC in measuring the service ranking, we developed a new metric, called the difference degree, to evaluate the quality of a ranking prediction with respect to the actual order. The difference degree, noted as D^{D}, is defined to compare our ranked service list and the baseline list by:

$$D^{\mathrm{D}} = \sum_{i=1}^{N} \left| d_i^{\mathrm{D}} \right| = \sum_{i=1}^{N} \frac{|R_i - B_i|}{B_i}, \tag{31}$$

where R_i represents the ranking order of s_i obtained by the proposed approach; B_i represents the order of s_i in the baseline list; d_i^{D} represents the relative difference of s_i. Obviously, a smaller D^{D} means a better accuracy.

Taking the baseline trustworthiness rankings {3, 1, 2, 5, 4, 6} and two predicted trustworthiness ranking, {1, 2, 3, 5, 4, 6} and {3, 1, 2, 4, 6, 5}, for example, the D^{D} value of the first ranking is 2.1667 and the second one is 0.8667. The calculation result clearly indicates that the second predicted ranking is much better than the first one, as the top 3 elements in the second ranking are identical to the baseline ranking.

7.3. Experiment in risk-sensitive application scenario

Example 1. Assume that a large-scale stock exchange corporation is ready to purchase a cloud service to store massive amounts of stock trading data. This service should have fairly high trustworthiness with a high performance-cost ratio and low potential risks. Considering that the peak stock trading time is from 9:30 AM to 11:30 AM and from 1:00 PM to 3:00 AM every working day, the trustworthiness evaluation of the cloud service is more important during these two periods than in other periods.

Based on this analysis of the user's requirements, we define the period preferences and the tradeoff coefficients for the current user, as shown in Table 3.

Then, we calculate the comprehensive ranking similarity between the current user and every candidate user based on the evaluations of training services by Eq. (20). By setting the different threshold values of user similarity δ^{th}, we get the different top-K neighboring users for the current user by Eq. (21). Based on the evaluation data from candidate services provided by the neighboring users, the original data is transformed into INNs. Table 4 shows the preprocessed evaluation data of candidate services #741–#748, denoted as s_1–s_8, when $\delta^{\mathrm{th}} = 0.5$.

The net superiority values of the candidate services are obtained by Eq. (28) when δ^{th} is set with the different values shown in Table 5. In Table 5, $|U^{\mathrm{N}}|$ is the total number of neighboring users.

The predicted ranking results are shown in Table 6.

Table 6 shows that the prediction results are distinctly different when the similarity threshold is set as a different value. By calculating the baseline sort values of candidate services with Eq. (30), we get the ranked services list shown in Table 7.

Table 7 demonstrates that the actual ranked list of candidate services is $s_3 \succ s_2 \succ s_8 \succ s_7 \succ s_1 \succ s_5 \succ s_6 \succ s_4$. Next, we employ the KRCC and difference degree to measure the quality of prediction when δ^{th} is set with a different value shown in Table 8.

Table 8 displays that the prediction results are identical with the baseline ranking when $\delta^{\mathrm{th}} = 0.50$ or $\delta^{\mathrm{th}} = 0.55$. Moreover, in most of the cases, the proposed approach can ensure that the sort

Table 4
Preprocessed evaluation data of candidate services expressed by INNs when $\delta^{\mathrm{th}} = 0.5$ in Example 1.

T	p_1						p_2						p_3					
	O_1		U_1		R_1		O_2		U_2		R_2		O_3		U_3		R_3	
T_1	0.97	0.99	0.00	0.23	0.00	0.00	0.96	0.99	0.00	0.18	0.00	0.00	0.40	0.91	0.00	0.26	0.00	0.00
T_2	0.99	0.99	0.00	0.10	0.00	0.00	0.99	0.99	0.00	0.06	0.00	0.00	0.88	1.00	0.00	0.05	0.00	0.00
T_3	0.99	0.99	0.00	0.11	0.00	0.00	0.99	0.99	0.00	0.06	0.00	0.00	0.89	1.00	0.00	0.05	0.00	0.00
T_4	0.00	1.00	0.71	1.00	0.00	1.00	0.00	1.00	0.62	1.00	0.00	0.91	0.55	0.98	0.01	0.29	0.00	0.00
T_5	0.94	1.00	0.01	0.53	0.00	0.01	0.93	1.00	0.03	0.57	0.00	0.01	0.27	0.99	0.01	0.37	0.00	0.01
T_6	0.94	0.99	0.04	0.58	0.00	0.02	0.90	1.00	0.08	0.96	0.00	0.06	0.00	0.84	0.04	0.55	0.00	0.02
T_7	0.98	0.99	0.00	0.06	0.00	0.00	0.98	0.99	0.00	0.10	0.00	0.00	0.83	0.94	0.00	0.05	0.00	0.00
T_8	0.98	0.99	0.00	0.06	0.00	0.00	0.98	0.99	0.00	0.08	0.00	0.00	0.82	0.95	0.00	0.06	0.00	0.00

T	p_4						p_5						p_6					
	O_4		U_4		R_4		O_5		U_5		R_5		O_6		U_6		R_6	
T_1	0.42	0.84	0.00	0.20	0.00	0.00	0.46	0.81	0.00	0.20	0.00	0.00	0.39	0.82	0.01	0.26	0.00	0.00
T_2	0.85	0.97	0.00	0.05	0.00	0.00	0.79	0.92	0.00	0.07	0.00	0.00	0.73	0.96	0.00	0.16	0.00	0.00
T_3	0.85	0.97	0.00	0.05	0.00	0.00	0.80	0.92	0.00	0.06	0.00	0.00	0.63	1.00	0.03	0.43	0.00	0.01
T_4	0.36	1.00	0.04	0.52	0.00	0.02	0.46	0.95	0.02	0.44	0.00	0.01	0.65	0.88	0.00	0.14	0.00	0.00
T_5	0.00	0.97	0.00	0.44	0.00	0.00	0.00	1.00	0.04	0.66	0.00	0.02	0.00	0.97	0.01	0.51	0.00	0.00
T_6	0.10	0.74	0.00	0.28	0.00	0.00	0.24	0.74	0.01	0.32	0.00	0.00	0.13	0.77	0.01	0.35	0.00	0.00
T_7	0.78	0.90	0.00	0.06	0.00	0.00	0.78	0.87	0.00	0.06	0.00	0.00	0.79	0.88	0.00	0.05	0.00	0.00
T_8	0.79	0.91	0.00	0.05	0.00	0.00	0.79	0.88	0.00	0.05	0.00	0.00	0.79	0.89	0.00	0.05	0.00	0.00

Table 5
Net superiority values of candidate services in Example 1.

δ^{th}	$\lvert U^N \rvert$	Net superiority values of candidate services							
		s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
0.20	44	−1.8438	3.6191	6.2802	−6.4595	−4.2575	−3.4392	2.3086	3.7921
0.25	34	−1.8128	3.7031	7.0000	−6.8292	−3.7096	−3.6485	2.1744	3.1224
0.30	29	−2.6177	4.5715	6.6480	−6.8464	−2.5777	−3.9582	1.8937	2.8868
0.35	24	−2.9126	4.5768	6.6481	−6.8490	−2.2405	−3.9979	1.9008	2.8743
0.40	21	−1.6225	3.5336	6.2670	−6.4493	−5.1136	−2.8145	2.5052	3.6942
0.45	17	−1.8439	3.0070	7.0000	−6.4497	−5.1136	−2.5928	1.9791	4.0138
0.50	13	−1.0000	5.0000	7.0000	−4.8024	−4.4529	−5.7447	1.4227	2.5773
0.55	11	−1.5256	5.0000	7.0000	−3.1711	−4.9237	−6.3796	1.5982	2.4018
0.60	5	−2.3060	5.7465	5.4073	−2.3395	−5.7877	−5.5667	1.3940	3.4522
0.65	2	−2.2698	5.6904	5.6242	−3.4319	−5.7167	−4.5816	1.2563	3.4291

Table 6
Predicted ranking results in Example 1.

δ^{th}	Candidate services							
	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
0.20	5	2	1	8	7	6	4	3
0.25	5	2	1	8	7	6	4	3
0.30	6	2	1	8	5	7	4	3
0.35	6	2	1	8	5	7	4	3
0.40	5	3	1	8	7	6	4	2
0.45	5	3	1	8	7	6	4	2
0.50	**5**	**2**	**1**	**8**	**6**	**7**	**4**	**3**
0.55	**5**	**2**	**1**	**8**	**6**	**7**	**4**	**3**
0.60	5	1	2	6	8	7	4	3
0.65	5	1	2	6	8	7	4	3

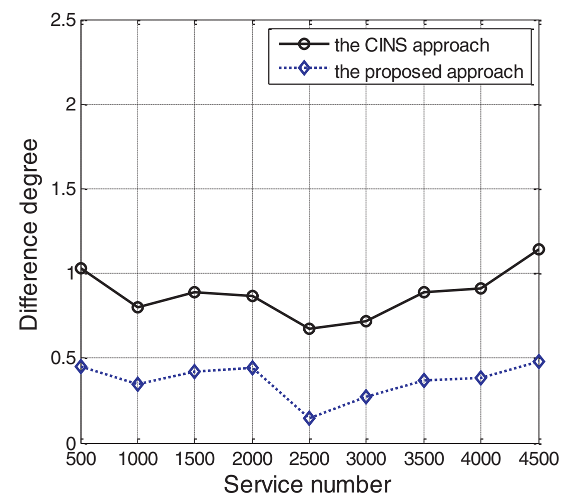

Fig. 4. Comparison of two approaches in Example 1.

order of the top 4 services in our ranked list is identical to the baseline list. By dynamically adjusting the user similarity threshold, the proposed approach can explore the optimal prediction result in which $D^D = 0$. The CINS approach introduced in the previous research [12] cannot ensure the optimal prediction result, and the minimum difference degree obtained by the CINS approach is 0.6524 in Example 1.

To demonstrate the superiority of the proposed approach in comparison to the CINS approach in Example 1, we perform the following experiments as follows. The user #9 is still viewed as the current user. The first experiment uses services #1–#500, and the second one uses services #501–#1000, and the remainder will continue to add another 500 services until all the 4500 services have been used. In every experiment, 8 candidate services are selected from 500 available services, and the threshold of user similarity is set with a known optimal value by adjusting dynamically it. The trustworthiness ranking of candidate services is predicted and the average difference degree between the baseline ranking and the predicted ranking are calculated based on 50 trials. The experiment result is shown in Fig. 4.

Fig. 4 demonstrates that the proposed approach can achieve a better prediction quality than the CINS approach. Compared to the CINS approach, the proposed approach approximately reduces 58.83 percent of the average difference degree. The main reason is that the proposed approach employs KRCC-based ranking analysis to accurately measure the similarity of preferences between users in regard to a set of cloud services, and the optimal similarity threshold ensures that the valuable evaluation data from the neighboring users produces good prediction results. Fig. 4 also displays that both the proposed approach and the CINS approach gains the best prediction quality when services #2000–#2500 are

Table 7
Baseline sort value and baseline ranking of candidate services in Example 1.

Candidate service	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
Baseline sort value	0.0139	0.3234	1.0000	0.0000	0.0102	0.0066	0.0414	0.0470
Baseline ranking order	5	2	1	8	6	7	4	3

Table 8
Quality of predictions in Example 1.

Quality of prediction	δ^{th}									
	0.20	0.25	0.30	0.35	0.40	0.45	**0.50**	**0.55**	0.60	0.65
KRCC	0.9286	0.9286	0.9286	0.9286	0.8571	0.8571	**1.0000**	**1.0000**	0.7143	0.7143
D^D	0.3096	0.3096	0.3667	0.3667	1.1429	1.1429	**0.0000**	**0.0000**	2.0833	2.0833

Table 9
Period preferences and tradeoff coefficients in Example 2.

W						D		
w_1	w_2	w_3	w_4	w_5	w_6	α	β	γ
0.10	0.10	0.20	0.25	0.25	0.10	0.55	0.10	0.35

used in the experiments. The reason is that the data dispersion of these services is smaller than other services, the coefficients of variation of them also showed this in Fig. 3.

7.4. Experiment in performance-cost-sensitive application scenario

Example 2. Assume that a logistics company is preparing to purchase a cloud host service to deploy their express delivery query application. The budget is very limited, and no highly confidential data is involved in this application. Therefore, the company desires the performance-cost ratio of the cloud host service to be as high as possible, on the premise that the potential risks are sufficiently low. The anticipated peak of visiting time for this application is from 9:00 AM to 5:00 PM every working day.

Based on this analysis of the user's requirements, we identify the period preferences and the tradeoff coefficients for the current user, as shown in Table 9.

Then, we calculate the comprehensive ranking similarity between the current user and every candidate user based on the evaluation data from the training services. By changing user similarity threshold, we get the different neighboring users for the current user. On the basis of evaluation data from candidate services, the original data is transformed into INNs. Table 10 shows the preprocessed evaluation data of the candidate services when $\delta^{\text{th}} = 0.75$.

As shown in Table 11, the net superiority values of candidate services can be obtained when δ^{th} is set with different values. The predicted ranking results are shown in Table 12. By calculating the baseline sort values of candidate services, we get the ranked services list shown in Table 13. Table 13 demonstrates that the actual ranked list of candidate services is $s_2 \succ s_3 \succ s_8 \succ s_7 \succ s_1 \succ s_5 \succ s_6 \succ s_4$.

We employ the KRCC and difference degree to measure the quality of prediction. The result is shown in Table 14. Table 14 demonstrates that the proposed approach can get the best quality of prediction in which $D^{\text{D}} = 0.5595$, when $\delta^{\text{th}} = 0.75$. The minimum difference degree obtained by the CINS approach is 0.6857 in Example 2 [12].

In the following experiments, we analyze the superiority of the proposed approach in comparison to the CINS approach in Example 2. The experiment setup is similar to Example 1. The experimental result is shown in Fig. 5. Compared to the CINS approach, the proposed approach approximately reduces 38.30 percent of the average difference degree.

Fig. 5 also demonstrates that the proposed approach can achieve a better prediction quality than the CINS approach.

7.5. Experiment in low price competition application scenario

Example 3. Assume that service #5 adopts a low price strategy by offering different discounts from 10 to 50% to improve its performance-cost ratio. In this case, we can again utilize the proposed approach to assist the stock exchange corporation in Example 1 and the logistics company in Example 2 to make decisions. Tables 15 and 16 are the preprocessed evaluation data of service #5 when $\delta^{\text{th}} = 0.50$ in Example 1 and when $\delta^{\text{th}} = 0.75$ in Example 2, respectively.

Table 10
Preprocessed evaluation data of candidate services expressed by INNs when $\delta^{\text{th}} = 0.75$ in Example 2.

T	p_1						p_2						p_3					
	O_1		U_1		R_1		O_2		U_2		R_2		O_3		U_3		R_3	
T_1	0.97	0.99	0.01	0.26	0.00	0.00	0.96	0.98	0.00	0.14	0.00	0.00	0.45	0.85	0.00	0.19	0.00	0.00
T_2	0.99	1.00	0.00	0.13	0.00	0.00	0.99	0.99	0.00	0.05	0.00	0.00	0.88	1.00	0.00	0.05	0.00	0.00
T_3	0.99	1.00	0.00	0.13	0.00	0.00	0.98	0.99	0.00	0.05	0.00	0.00	0.90	0.99	0.00	0.03	0.00	0.00
T_4	0.00	1.00	0.72	1.00	0.00	1.00	0.00	1.00	0.56	1.00	0.00	0.82	0.71	0.90	0.00	0.07	0.00	0.00
T_5	0.95	1.00	0.01	0.49	0.00	0.00	0.92	1.00	0.00	0.51	0.00	0.00	0.15	0.96	0.00	0.32	0.00	0.00
T_6	0.96	0.98	0.00	0.24	0.00	0.00	0.95	0.97	0.00	0.24	0.00	0.00	0.00	0.75	0.02	0.38	0.00	0.01
T_7	0.99	0.99	0.00	0.05	0.00	0.00	0.98	0.99	0.00	0.02	0.00	0.00	0.84	0.90	0.00	0.02	0.00	0.00
T_8	0.99	0.99	0.00	0.05	0.00	0.00	0.98	0.99	0.00	0.02	0.00	0.00	0.83	0.91	0.00	0.04	0.00	0.00

T	p_4						p_5						p_6					
	O_4		U_4		R_4		O_5		U_5		R_5		O_6		U_6		R_6	
T_1	0.52	0.84	0.00	0.12	0.00	0.00	0.35	0.77	0.00	0.15	0.00	0.00	0.39	0.78	0.00	0.18	0.00	0.00
T_2	0.89	1.00	0.00	0.04	0.00	0.00	0.79	0.93	0.00	0.06	0.00	0.00	0.77	0.88	0.00	0.05	0.00	0.00
T_3	0.89	1.00	0.00	0.04	0.00	0.00	0.82	0.92	0.00	0.04	0.00	0.00	0.46	1.00	0.05	0.57	0.00	0.02
T_4	0.66	0.91	0.00	0.09	0.00	0.00	0.24	1.00	0.03	0.49	0.00	0.02	0.58	0.82	0.00	0.16	0.00	0.00
T_5	0.00	0.98	0.00	0.37	0.00	0.00	0.00	0.93	0.01	0.40	0.00	0.00	0.00	0.89	0.01	0.45	0.00	0.00
T_6	0.16	0.71	0.00	0.25	0.00	0.00	0.19	0.58	0.00	0.15	0.00	0.00	0.14	0.65	0.00	0.28	0.00	0.00
T_7	0.83	0.90	0.00	0.02	0.00	0.00	0.74	0.83	0.00	0.04	0.00	0.00	0.74	0.80	0.00	0.02	0.00	0.00
T_8	0.84	0.91	0.00	0.02	0.00	0.00	0.76	0.83	0.00	0.02	0.00	0.00	0.74	0.80	0.00	0.02	0.00	0.00

Table 11
Net superiority values of candidate services in Example 2.

δ^{th}	$\|U^N\|$	Net superiority values of candidate services s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
0.35	65	−3.7223	3.6407	2.9728	−4.1449	−6.0960	−2.0368	5.5064	3.8800
0.40	60	−3.2808	4.3085	3.7568	−4.2825	−5.9892	−2.4475	5.0409	2.8938
0.45	57	−2.1035	4.8119	3.0488	−3.7348	−6.3310	−3.8307	5.1691	2.9702
0.50	50	−1.8216	4.0315	3.7584	−3.2859	−4.1571	−6.3521	3.6709	4.1560
0.55	44	−2.5625	3.6487	3.9305	−3.1986	−3.7679	−6.1478	4.6614	3.4360
0.60	33	−1.5916	6.3222	3.1317	−3.6541	−5.1930	−5.4336	3.7853	2.6332
0.65	24	−2.4642	5.9449	3.5598	−4.0770	−4.9069	−4.4448	2.1687	4.2195
0.70	16	−1.5210	6.1096	3.1156	−3.2934	−5.5335	−5.3067	2.1941	4.2353
0.75	7	−1.6237	6.2370	3.5440	−3.3454	−4.9658	−5.6248	2.4427	3.3360
0.80	3	−4.1190	5.2859	6.7141	−3.5324	−3.2778	−5.0708	1.0000	3.0000

Table 12
Predicted ranking results in Example 2.

δ^{th}	Candidate services s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
0.35	6	3	4	7	8	5	1	2
0.40	6	2	3	7	8	5	1	4
0.45	5	2	3	6	8	7	1	4
0.50	5	2	3	6	7	8	4	1
0.55	5	3	2	6	7	8	1	4
0.60	5	1	3	6	7	8	2	4
0.65	5	1	3	6	8	7	4	2
0.70	5	1	3	6	8	7	4	2
0.75	**5**	**1**	**2**	**6**	**7**	**8**	**4**	**3**
0.80	7	2	1	6	5	8	4	3

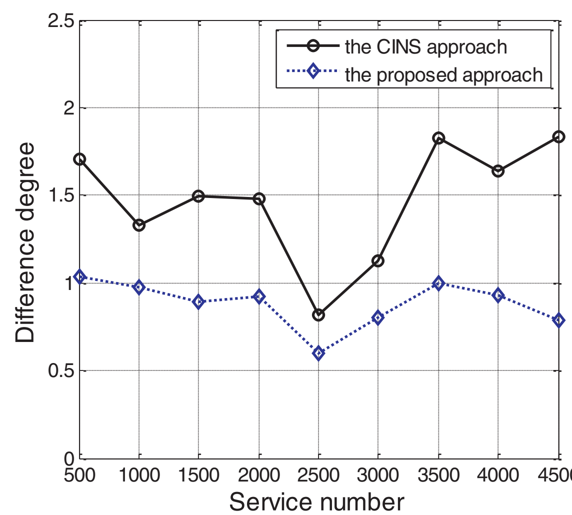

Fig. 5. Comparison of two approaches in Example 2.

Table 17 displays the sort values of candidate services in the low price competition application scenario for comparative analysis. Obviously, service #5 fails to increase its probability to obtain a distinct advantage although it achieves an attractive performance-cost ratio in every period. The proposed approach consistently maintains the absolute dominance of service #3 for the stock exchange corporation and the advantage of service #2 for the logistics company.

7.6. Analysis and discussion

These experiments illustrate the merits of the proposed approach as follows:

(1) Flexibly customizing the user preferences for different periods in the light of the actual demands facilitates to improve the consumer satisfaction. The users will be no more confused when submitting their preferences. In the proposed approach, the period preferences and the tradeoff coefficients have become the mutually independent parameters, and then we can simplify the MCDM procedure based on INS theory. In Example 1, the evaluations of service #3 is far from outstanding in period #1 and period #6 in comparison with service #2, but service #3 becomes the optimal candidate by relying on its advantages in period #3 and period #4. The stock exchange corporation does not care at all about period #1 and period #6, while period #3 and period #4 cover the period of stock exchange. A precise analysis of the period preferences helps users to find the most trustworthy candidate service.

(2) Supporting the tradeoffs between performance-cost and potential risks in multiple periods can produce different trustworthiness ranking results for different application scenarios. In the risk-sensitive application scenario of Example 1,

Table 13
Baseline sort value and baseline ranking of candidate services in Example 2.

Candidate service	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
Baseline sort value	0.0240	1.0000	0.3020	0.0000	0.0128	0.0110	0.0662	0.0741
Baseline ranking order	5	1	2	8	6	7	4	3

Table 14
Quality of predictions in Example 2.

Quality of prediction	δ^{th} 0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	**0.75**	0.80
KRCC	0.4286	0.5714	0.5714	0.7143	0.5714	0.7143	0.7143	0.7143	**0.8571**	0.7143
D^D	5.0274	3.5274	3.1667	2.7262	3.6429	1.8929	1.4167	1.4167	**0.5595**	2.4595

Table 15
Preprocessed evaluation data of service #5 with discounts expressed by INNs when $\delta^{\text{th}} = 0.50$ in Example 1.

Discount (%)	T_1						T_2						T_3						T_4						T_5						T_6					
	O		U		R		O		U		R		O		U		R		O		U		R		O		U		R		O		U		R	
10	1.00	1.00	0.01	0.53	0.00	0.01	1.00	1.00	0.03	0.57	0.00	0.01	0.30	1.00	0.01	0.37	0.00	0.01	0.00	1.00	0.00	0.44	0.00	0.00	0.00	1.00	0.04	0.66	0.00	0.02	0.00	1.00	0.01	0.51	0.00	0.00
20	1.00	1.00	0.01	0.53	0.00	0.01	1.00	1.00	0.03	0.57	0.00	0.01	0.34	1.00	0.01	0.37	0.00	0.01	0.00	1.00	0.00	0.44	0.00	0.00	0.00	1.00	0.04	0.66	0.00	0.02	0.00	1.00	0.01	0.51	0.00	0.00
30	1.00	1.00	0.01	0.53	0.00	0.01	1.00	1.00	0.03	0.57	0.00	0.01	0.38	1.00	0.01	0.37	0.00	0.01	0.00	1.00	0.00	0.44	0.00	0.00	0.00	1.00	0.04	0.66	0.00	0.02	0.00	1.00	0.01	0.51	0.00	0.00
40	1.00	1.00	0.01	0.53	0.00	0.01	1.00	1.00	0.03	0.57	0.00	0.01	0.45	1.00	0.01	0.37	0.00	0.01	0.00	1.00	0.00	0.44	0.00	0.00	0.00	1.00	0.04	0.66	0.00	0.02	0.00	1.00	0.01	0.51	0.00	0.00
50	1.00	1.00	0.01	0.53	0.00	0.01	1.00	1.00	0.03	0.57	0.00	0.01	0.54	1.00	0.01	0.37	0.00	0.01	0.00	1.00	0.00	0.44	0.00	0.00	0.00	1.00	0.04	0.66	0.00	0.02	0.00	1.00	0.01	0.51	0.00	0.00

Table 16
Preprocessed evaluation data of service #5 with discounts expressed by INNs when $\delta^{\text{th}} = 0.75$ in Example 2.

Discount (%)	T_1						T_2						T_3						T_4						T_5						T_6					
	O		U		R		O		U		R		O		U		R		O		U		R		O		U		R		O		U		R	
10	1.00	1.00	0.01	0.49	0.00	0.00	1.00	1.00	0.00	0.51	0.00	0.00	0.16	1.00	0.00	0.32	0.00	0.00	0.00	1.00	0.00	0.37	0.00	0.00	0.00	1.00	0.01	0.40	0.00	0.00	0.00	0.99	0.01	0.45	0.00	0.00
20	1.00	1.00	0.01	0.49	0.00	0.00	1.00	1.00	0.00	0.51	0.00	0.00	0.18	1.00	0.00	0.32	0.00	0.00	0.00	1.00	0.00	0.37	0.00	0.00	0.00	1.00	0.01	0.40	0.00	0.00	0.00	1.00	0.01	0.45	0.00	0.00
30	1.00	1.00	0.01	0.49	0.00	0.00	1.00	1.00	0.00	0.51	0.00	0.00	0.21	1.00	0.00	0.32	0.00	0.00	0.00	1.00	0.00	0.37	0.00	0.00	0.00	1.00	0.01	0.40	0.00	0.00	0.00	1.00	0.01	0.45	0.00	0.00
40	1.00	1.00	0.01	0.49	0.00	0.00	1.00	1.00	0.00	0.51	0.00	0.00	0.24	1.00	0.00	0.32	0.00	0.00	0.00	1.00	0.00	0.37	0.00	0.00	0.00	1.00	0.01	0.40	0.00	0.00	0.00	1.00	0.01	0.45	0.00	0.00
50	1.00	1.00	0.01	0.49	0.00	0.00	1.00	1.00	0.00	0.51	0.00	0.00	0.29	1.00	0.00	0.32	0.00	0.00	0.00	1.00	0.00	0.37	0.00	0.00	0.00	1.00	0.01	0.40	0.00	0.00	0.00	1.00	0.01	0.45	0.00	0.00

Table 17
Comparative analysis in a low price competition application scenario.

Application scenario	Discount (%)	Candidate services								Ranking order of s_1	Ranking order in baseline
		s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8		
Stock exchange corporation	10	−1.0000	5.0000	7.0000	−4.9679	**−4.2698**	−5.7622	1.4227	2.5773	6	6
	20	−1.0000	5.0000	7.0000	−4.9807	**−4.2539**	−5.7654	1.4226	2.5774	6	6
	30	−1.0000	5.0000	7.0000	−4.999	**−4.2316**	−5.7694	1.4224	2.5776	6	6
	40	−1.0000	5.0000	7.0000	−5.0274	**−4.1981**	−5.7745	1.4221	2.5779	6	6
	50	−1.0000	5.0000	7.0000	−5.044	**−4.1751**	−5.7809	1.4214	2.5786	6	6
Logistics company	10	−2.4959	6.2369	3.5468	−3.6261	**−3.2426**	−5.8441	2.2126	3.2124	6	6
	20	−2.4966	6.2369	3.5475	−3.6253	**−3.2426**	−5.8441	2.2127	3.2116	6	6
	30	−2.4977	6.2369	3.5486	−3.6242	**−3.2426**	−5.8441	2.2129	3.2103	6	6
	40	−2.4993	6.2369	3.5502	−3.6227	**−3.2416**	−5.8452	2.2131	3.2085	6	6
	50	−2.5017	6.2369	3.5527	−3.6202	**−3.2328**	−5.854	2.2134	3.2057	6	6

the assessment of potential risks plays a more important role than the performance-cost ratio in evaluating candidate services. This assessment leads to service #3 to be judged as the most trustworthy candidate. However, the performance-cost-sensitive application scenario of Example 2 shows an entirely different prediction result, in which service #2 becomes the most trustworthy candidate.

(3) The proposed approach can effectively prevent the low-quality services with high performance-cost ratio from achieving an absolute advantage in competition with other services. In practice, some service providers adopt the low-price strategy for dramatically increasing the performance-cost ratio of low-quality services. In the proposed approach, the low-price strategy can boost the popularity of low-quality services to some extent, but it does not help these services to dominate their competition based solely on a malignant price war. As shown in Tables 15 and 16, one service with high marks in the assessment of potential risks and uncertainty is unlikely to be a highly trustworthy candidate. Table 17 demonstrates that service #5 does not earn the ideal sort value in Example 3.

(4) The proposed approach is capable of improving the quality of ranking prediction by exactly identifying the neighboring users. In the uncertain cloud environment, in order to accurately measure the similarity of preferences between different users in regard to a set of cloud services, the KRCC-based ranking analysis method can foster a better result than other methods directly based on the imprecise evaluation data. Tables 8 and 14 demonstrate that the quality of the trustworthiness ranking predictions can be upgraded by adjusting the user similarity threshold. Moreover, if there is enough original evaluation data, the ideal value of the user similarity threshold can be obtained by the limited trials. Figs. 4 and 5 indicate that the ranking predictions of the proposed method are more accurate than the previous approach based on CINS.

8. Conclusions and further study

In an uncertain cloud environment, the fluctuating QoS, flexible service pricing and complicated potential risks have always presented challenges to service selection. Aiming at the deficiency of the traditional value prediction approaches, this paper utilizes the INS theory to propose a time-aware trustworthiness ranking prediction approach to selecting the highly trustworthy cloud service meeting the user-specific requirements. To support the trade-offs between performance-costs and potential risks during multiple periods, we put forward the new INS operators with the theoretical proofs provided to calculate the possibility degree and ranking value of trustworthiness INNs. These operators contribute significantly to the identification of neighboring users based on the KRCC. The problem of time-aware trustworthiness ranking prediction is formulated as an MCDM problem of creating a ranked services list using the INS theory, and an improved ELECTRE method is developed to solve it. The experiments based on a real-world dataset illustrate that the proposed approach can enhance the accuracy of prediction by about 58.83 percent in the risk-sensitive application scenario and 38.30 percent in the performance-cost-sensitive application scenario compared to the existing approach, and also can effectively prevent the malignant price competition launched by low-quality services.

Although this paper presents a promising solution from the perspective of the time series analysis for the trustworthiness ranking prediction in the cloud environment, this problem is still an open question. In this paper, only the limited evaluation data are exploited in the experiments, but more information from more users and timeslots may make for improving the quality of trustworthiness ranking prediction. Especially, in the big data environment, some issues, such as the preprocessing mechanisms of the original evaluations, the assessment modes of history trustworthiness data and the execution performance of core algorithms, require the deep-going studies in the future.

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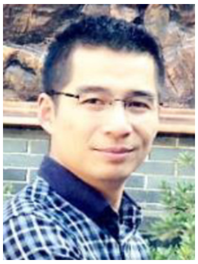

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