



Toward trustworthy cloud service selection: A time-aware approach using interval neutrosophic set



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HIGHLIGHTS

- Propose a time-aware service selection approach for uncertain cloud industry.
- Formulate a multi-criterion decision-making problem using interval neutrosophic set.
- Support tradeoffs between performance–costs and potential risks in time periods.
- Establish the CINS theory to calculate and compare the candidate cloud services.
- Develop a CINS ranking method to create a ranked list of trustworthy cloud services.

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ABSTRACT

Cloud services consumers face a critical challenge in selecting trustworthy services from abundant candidates, and facilitating these choices has become a critical issue in the uncertain cloud industry. This paper employs the time series analysis to address challenges resulting from fluctuating quality of service, flexible service pricing and complicated potential risks in order to propose a time-aware trustworthy service selection approach with tradeoffs between performance–costs and potential risks. The original evaluation data about the services is preprocessed using a cloud model, and interval neutrosophic set (INS) theory is utilized to describe and measure the performance–costs and potential risks of services. In order to calculate and compare the candidate services while supporting tradeoffs between performance–costs and potential risks in different time periods, we established a cloud service interval neutrosophic set (CINS) and designed its operators and calculation rules, with theoretical proofs provided. The problem of time-aware trustworthy service selection is formulated as a multi-criterion decision-making (MCDM) problem of creating a ranked services list using CINS, and it is solved by developing a CINS ranking method. Finally, experiments based on a real-world dataset illustrate the practicality and effectiveness of the proposed approach.

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1. Introduction

1.1. Motivation

Recently, cloud computing has been gaining enormous momentum. Cloud service providers around the world have publicized many services [7]. Increasing numbers of cloud service consumers find the convenience and affordability of cloud services alluring;

however, the rapid proliferation of cloud services draws consumers into the dilemma of service selection, especially when multiple services provide similar functionalities. This dilemma has created a critical issue in cloud computing field, that of facilitating cloud service consumers to select trustworthy services with tradeoffs between performance–costs and potential risks [29] among abundant candidates. This task includes the following challenges:

- (1) The quality of service (QoS) of cloud services generally fluctuates within a certain range due to the dynamic cloud environment. The quality of experience [27] for consumers is often different from the QoS claimed by service providers. According to the evaluation reports [80] of cloud hosts in China, the performance of services varies widely. In some key

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indicators, such as network throughput and memory speed, the maximum measured value is ten times more than the minimum. The real QoS experienced by consumers can be influenced by factors such as client device type, network location and context [54,83,77]. In previous experiments [40] based on real-world WS-DREAM dataset #2 [88], we analyzed the response time for 5,825 services collected from 339 users, and found that the coefficients of variation for most of services exceed 1.0. As these data illustrate, how to accurately measure the uncertainty of QoS combining the feedback data [40] from consumers, continuous monitoring data [15] or auditing data [36] from service providers, and continuous evaluation data from third parties [80,12,10], has become a key problem in the cloud environment.

- (2) Although the load-balancing strategies have been implemented in cloud platforms [34], the load conditions for cloud services may be quite different from one another based on different networks or geographical locations. Within a specified time period, some services are possible under a heavy load, while others might only be possibly under a light load, giving consumers different quality of experience. In order to balance loads, improve energy efficiency and maximize profits, service providers are likely to adopt flexible pricing over time for cloud services [78,48,53]. For example, a service might offer a considerable discount during its light load time period to attract more consumers, or charge additional fees during a time period that is highly volatile in user interaction. Moreover, consumers might in practice attach particular importance to specific time periods according to their application requirements, or purchase a service despite its poor performance during time periods that are less important to them. Therefore, identifying the different performance and cost of service in time periods is of great significance for consumers distinguishing among candidates.
- (3) Over the past few years, security problems have increasingly emerged in cloud services, such as Salesforce services, EC2 services, BPOS services, SONY Playstation services and iCloud services. These events have proven that cloud computing is fraught with potential risks that must be carefully evaluated prior to engagement [19]. Recently the risk assessment in cloud services has attracted concern from some organizations, including Cloud Security Alliance (CSA) [13], China Cloud Computing Promotion and Policy Forum (3CPP) [10], and researchers [81,22]. Some primary potential risks to cloud services have been identified and analyzed [17,32]. Especially, recognized as the important risks inherent to the cloud, the availability [6,56] of cloud services and the disruption or failure of cloud computing network [49] are vulnerable to the heavy load and networks' susceptibility in specified time periods. In contrast to performance and costs of cloud services, these potential risks inherent to the cloud are more uncertain. The assessment of potential risks over multiple time periods adds extra complexity to trustworthy service selection problem.

In real-world applications, both the performance–costs and some potential risks of cloud services are dynamic and uncertain during different time periods. Naturally, consumers hope to select the most trustworthy cloud service among abundant candidates by considering the tradeoffs between performance–costs and potential risks over multiple time periods. Consumers may pay less attention to potential risks when performance–cost is more important to them, and may pay less attention to performance–cost during times of sensitivity to potential risks. In order to achieve higher performance–costs in cloud services, consumers can change the time periods of their usage, or they may pay more to enjoy better performance during specific time periods. This paper targets the research tasks of (1) accurately describing

and measuring the performance–costs and potential risks of cloud services as a whole, with consideration of uncertainty, and (2) calculating and comparing candidate services with tradeoffs between performance–costs and potential risks, according to the requirements of different application scenarios during different time periods.

1.2. Our contributions

In this paper, to measure the uncertainty of cloud environment, we have adopted a new theory known as interval neutrosophic set (INS) [67,84], which is a generalization of classical, three-valued and fuzzy logic. The assessment data of cloud services and the user's application requirements are integrated and transformed into INS. Every service is measured from three aspects, namely performance–costs, potential risks and their uncertainty, which are equivalent to the truth-membership, falsity-membership and indeterminacy-membership, respectively, in INS. The services with high performance–costs, low risks and uncertainty may become the trustworthy candidates. Our strategy for selecting trustworthy services from an abundant field of candidates involves formulating the problem of time-aware service selection with tradeoffs between performance–costs and potential risk as a multi-criterion decision-making (MCDM) problem that creates a ranked services list using INS theory.

The main contributions of this paper are as follows:

- (1) In order to measure the uncertainty of cloud services and compare candidate services with tradeoffs between performance–costs and potential risks, we propose the cloud service interval neutrosophic set (CINS), based on INS and combining the time period features of cloud services with the tradeoff coefficients from consumers. The aggregation operators and the entropy weight measure method for CINS are designed based on theoretical proofs.
- (2) We describe and assess the performance–costs and potential risks of cloud services by utilizing the cloud model and INS theory from the new perspective of time series analysis. Based on this assessment, we formulate the time-aware trustworthy cloud service selection problem with tradeoffs between performance–costs and potential risks over multiple time periods as a MCDM problem employing CINS theory. We then develop a CINS ranking approach to solve the MCDM problem.
- (3) We examine the proposed approach through experiments on a real-world dataset and an appropriate baseline for our comparative analysis. Results demonstrate that our approach can work effectively in the risk-sensitive service selection mode and the performance–cost-sensitive service selection mode, and also prevent malignant price competition launched by some low-quality services. This paper can provide decision support approach for time-aware trustworthy service selection problem.

The rest of this paper is organized as follows. Section 2 briefly introduces the related work. Section 3 defines neutrosophic set (NS), INS and CINS. Section 4 defines the problem. Section 5 presents the aggregation operators and the entropy weight measure method for CINS. Section 6 puts forward the time-aware trustworthy service selection approach. Section 7 analyzes the experiments and results. Finally, Section 8 presents conclusions.

2. Related works

2.1. Trustworthy cloud services selection

Facilitating users' selection of trustworthy candidates from a set of functionally equivalent cloud services represents an exciting

area of expansion for cloud computing research. Some approaches can provide effective decision supports for this problem as follows:

- (1) Approaches based on MCDM methods. 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 between solutions. MCDM methods can be used to solve the service selection problem, provided that the trustworthiness attributes and service candidates are finite. Techniques such as the analytic hierarchy process (AHP), analytic network process (ANP), fuzzy analytic hierarchy process (FAHP), ELECTRE and TOPSIS fall into this category. Godse et al. [20] presented an AHP-based SaaS service selection approach to score and rank services objectively; the incorporation of AHP can ameliorate judgmental product prioritization, making the process more rational than strictly subjective ratings. Garg et al. [18] employed an AHP method to measure attributes of QoS and rank cloud services. Similarly, Menzel et al. [43] introduced an ANP method for selecting IaaS services. Ma et al. [40] proposed a trustworthy cloud service selection approach that employs the FAHP method to calculate the weights of user features. Silas et al. [61] developed a cloud service selection middleware based on the ELECTRE method. Sun et al. [63] presented a multi-criteria decision-making technique based on fuzzy TOPSIS method to rank cloud services.
- (2) Approaches based on prediction. These approaches focus on how to predict the QoS of service accurately and select trustworthy service for users. Techniques such as the probability theory, fuzzy theory, evidence theory, social network analysis (SNA), etc., fall into this category. Mehdi et al. [42] presented a QoS-aware approach based on probabilistic models to assist the service selection, which allows consumers to maintain a trust model of each service provider they have interacted with for the prediction of the most trustworthy service. Qu et al. [51] proposed a system that evaluates trustworthiness of cloud services according to users' fuzzy QoS requirements and services' dynamic performances to facilitate service selection. Huo et al. [26] presented a fuzzy trustworthiness evaluation method combining Dempster–Shafer theory to solve the synthesis of evaluation information for cloud services. Mo et al. [44] put forward a cloud-based mobile multimedia recommendation system by collecting the user contexts, user relationships, and user profiles from video-sharing websites for generating recommendation rules. Targeting the objective and subjective characteristics of trustworthiness evaluations, Ding et al. [16] presented a trustworthiness evaluation framework of cloud services to predict QoS and customer satisfaction for selecting trustworthy services.
- (3) Approaches based on recommendation system technologies. These approaches exploit user preferences from history data and achieve personalized service recommendation. By integrating recommendation system technologies such as the collaborative filtering algorithm (CFA), service recommendations based on user feedback have become the dominant trend in trustworthy service selection. Ma et al. [38] presented a user preferences-aware recommendation approach for trustworthy cloud services, in which user preferences are identified by usage preference, trust preference and cost preference. Rosaci et al. [54] proposed an agent-based architecture to recommend multimedia services by integrating the content-based recommendation method and CFA. Wang et al. [66] presented a cloud service selection model employing service brokers to perform dynamic service selection based on an adaptive learning mechanism. Ma et al. [39] proposed a trustworthy service recommendation approach based on interval numbers of four

parameters by employing the similarity of client-side feature between potential user and consumers. In order to improve the prediction accuracy of CFA, Hu et al. [25] accounted for the factor of time by proposing a time-aware CFA to predict missing QoS values; this approach collects users' historic data about service at different time intervals and uses it to compute the degree of similarity between services and users. Zhong et al. [89] also proposed a time-aware service recommendation approach by extracting the time sequence of topic activities and the service-topic correlation matrix from service usage history, and forecasting topic evolution and service activity in the near future.

- (4) Approaches based on reputation mechanism. The trustworthiness of cloud services can affect the reputation of the service provider; in turn, a reputable service provider is more likely to produce highly trustworthy services. Therefore, evaluating and measuring the reputations of cloud service providers can aid in selecting trustworthy cloud services based on history, expertise and third-party data relevant to cloud service providers. Ramaswamy et al. [52] discussed an approach that utilizes the penalties, prize points and monitoring mechanism of mobile agents to ensure trustworthiness among the cloud broker, customer and service provider. Mouratidis et al. [45] presented a framework incorporating a modeling language that supports the elicitation of security and privacy requirements for selecting suitable service providers. Ayday et al. [5] incorporated belief propagation algorithm to evaluate reputation management systems, and employed factor graph to describe the interactive behavior between consumers and service providers. Pawar et al. [46] proposed an uncertainty model that employs subjective logic operators to calculate the reputations of service providers. Shen et al. [59] proposed a collaborative cloud computing platform, which incorporates multi-faceted reputation management, resource selection, and price-assisted reputation control.

2.2. Neutrosophic set theory

Since Zadeh proposed fuzzy set (FS) theory in 1965, many novel extensions have been proposed to settle issues surrounding imprecise, incomplete and uncertain information. These include the interval-valued fuzzy set (IVFS) [65], intuitionistic fuzzy sets (IFS) [3], interval-valued intuitionistic fuzzy sets (IVIFS) [4] and hesitant fuzzy sets (HFS) [64]. In classical set theory, an entity may have a certain degree of membership belonging to a set. As an extension, fuzzy set theory permits the gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the real unit interval $[0, 1]$. It also has a certain degree of non-membership, which is taken into consideration in IFS. In addition, HFS was introduced in order to cope with the situations that people are hesitant in expressing their preference over objects in a decision making process. Moreover, the applications of the extensions of FS in various fields have attracted considerable researchers' attention [28,60,47,69,68].

Based on the fact that IFSs cannot handle indeterminate information – that is, the zone of ignorance for a proposition's value between truth and falsity [74] – Smarandache [62] proposed neutrosophic logic and the neutrosophic set (NS). As the truth-membership, indeterminacy-membership, and false-membership in NS are independent, it is a set in which each element of the universe possesses degrees of truth, indeterminacy and falsity, whose values lie in the non-standard unit interval $]0^-, 1^+[$, which is an extension to IFS's standard interval $[0, 1]$. 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 [31], image segmentation [58,23,21,

85], artificial intelligence [2], growth and decline analysis of new economies [1] and financial dataset detection [33].

For the convenience of application of NS in practical application, Wang et al. [67] proposed an instance of NS called a single-valued neutrosophic set (SVNS). In turn, Ye [75] 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. [67] proposed the concept of INS and provided its set-theoretic operators.

NS has also been applied to MCDM problems. Ye [74] developed a MCDM approach using a SVNS correlation coefficient measurement. Zhang et al. [82] presented a new correlation coefficient measure of INS and a MCDM method is developed, which takes into account the influence of the evaluations' uncertainty and both the objective and subjective weights. In another study, Liu et al. [37] presented 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. [84] presented a outranking approach based on INS and ELECTRE IV for MCDM problems. Şahin et al. [55] proposed a MCDM method based on inclusion measure for INS.

To the best of our knowledge, no similar research has investigated cloud service interval neutrosophic set (CINS) theory and the MCDM method of modeling a trustworthy cloud service selection problem with tradeoffs between performance–costs and potential risks from the perspective of time series analysis.

3. Preliminary concepts

3.1. IN, NS, INS and their operators

This section introduces some basic concepts and definition utilized in the rest of the paper.

Definition 1 ([57,8,72]). Let $\tilde{a} = [a^L, a^U] = \{a^L \leq x \leq a^U\}$; then \tilde{a} is termed as an interval number (IN). If $0 \leq a^L \leq x \leq a^U$, then \tilde{a} is a positive interval number.

Definition 2 ([71]). Let $\tilde{a} = [a^L, a^U]$, $\tilde{b} = [b^L, b^U]$, $l_{\tilde{a}} = a^U - a^L$ and $l_{\tilde{b}} = b^U - b^L$; then the degree of possibility of $\tilde{a} \geq \tilde{b}$ is formulated by Eq. (1):

$$P(\tilde{a} \geq \tilde{b}) = \min\{|l_{\tilde{a}} + l_{\tilde{b}}|, \max(a^U - b^L, 0)\} / (l_{\tilde{a}} + l_{\tilde{b}}). \quad (1)$$

Suppose that there are n interval numbers $\tilde{a}_i = [a_i^L, a_i^U]$ ($i = 1, 2, \dots, n$), and each interval number \tilde{a}_i is compared with all interval numbers \tilde{a}_j ($j = 1, 2, \dots, n$) using Eq. (1). Then a complementary matrix, $P = \{p_{ij}\}$, can be constructed. $p_{ij} \geq 0$, $p_{ij} + p_{ji} = 1$, $p_{ii} = 0.5$. On the basis of P , the sort value of each interval number \tilde{a}_i can be calculated by Eq. (2):

$$o_i = \left(\sum_{j=1}^n p_{ij} + \frac{n}{2} - 1 \right) / (n(n-1)), \quad i = 1, 2, \dots, n. \quad (2)$$

Definition 3 ([62]). Let X be a space of points or objects, with a generic element in X denoted by x . A NS A in X is described using a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$. $T_A(x)$, $I_A(x)$ and $F_A(x)$ are real standard or nonstandard subsets of $]0^-, 1^+]$; that is, $T_A(x) : X \rightarrow]0^-, 1^+]$, $I_A(x) : X \rightarrow]0^-, 1^+]$ and $F_A(x) : X \rightarrow]0^-, 1^+]$. There is no restriction on the sum of $T_A(x)$, $I_A(x)$ and $F_A(x)$, so $0^- \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3^+$.

Definition 4 ([75]). Let X be a space of points or objects, with a generic element in X denoted by x . A NS A in X is characterized by $T_A(x)$, $I_A(x)$ and $F_A(x)$, which are singleton subintervals or subsets in the real standard $[0, 1]$; that is $T_A(x) : X \rightarrow [0, 1]$, $I_A(x) : X \rightarrow [0, 1]$ and $F_A(x) : X \rightarrow [0, 1]$. Then, a simplification of NS A is denoted by

$$A = \{ \langle x, T_A(x), I_A(x), F_A(x) \rangle | x \in X \},$$

which is a subclass of NS called a SNS.

Definition 5 ([67]). An INS A in X is characterized by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$. For each point x in X , it is true that

$$T_A(x) = [\inf T_A(x), \sup T_A(x)], \quad I_A(x) = [\inf I_A(x), \sup I_A(x)], \\ F_A(x) = [\inf F_A(x), \sup F_A(x)] \in [0, 1]$$

and $0 \leq \sup T_A + \sup I_A + \sup F_A \leq 3$, $x \in X$. Only the subunitary interval of $[0, 1]$ is considered, and it is a subclass of NS. Therefore, all INSs are clearly NSs.

Definition 6. Let two INSs $A = \langle [\inf T_A, \sup T_A], [\inf I_A, \sup I_A], [\inf F_A, \sup F_A] \rangle$ and $B = \langle [\inf T_B, \sup T_B], [\inf I_B, \sup I_B], [\inf F_B, \sup F_B] \rangle$, and $\lambda > 0$. The INS operations are defined below [67].

- (1) $A \oplus B = \langle [\inf T_A + \inf T_B - \inf T_A \cdot \inf T_B, \sup T_A + \sup T_B - \sup T_A \cdot \sup T_B], [\inf I_A \cdot \inf I_B, \sup I_A \cdot \sup I_B], [\inf F_A \cdot \inf F_B, \sup F_A \cdot \sup F_B] \rangle;$
- (2) $A \otimes B = \langle [\inf T_A \cdot \inf T_B, \sup T_A \cdot \sup T_B], [\inf I_A + \inf I_B - \inf T_A \cdot \inf I_B, \sup I_A + \sup I_B - \sup I_A \cdot \sup I_B], [\inf F_A + \inf F_B - \inf F_A \cdot \inf F_B, \sup F_A + \sup F_B - \sup F_A \cdot \sup F_B] \rangle;$
- (3) $\lambda \cdot A = \langle [1 - (1 - \inf T_A)^\lambda, 1 - (1 - \sup T_A)^\lambda], [(\inf I_A)^\lambda, (\sup I_A)^\lambda], [(\inf F_A)^\lambda, (\sup F_A)^\lambda] \rangle;$
- (4) $A^\lambda = \langle [(\inf T_A)^\lambda, (\sup T_A)^\lambda], [(\inf I_A)^\lambda, (\sup I_A)^\lambda], [(\inf F_A)^\lambda, (\sup F_A)^\lambda] \rangle.$

3.2. CINS and its operators

CINS is described in this section in order to measure the uncertainty of cloud services and compare candidate services with tradeoffs between performance–costs and potential risks.

Definition 7. The comprehensive evaluation of a cloud service is characterized by CINS $A = \langle \alpha_A O_A, \beta_A U_A, \gamma_A R_A \rangle$. $P_A = [\inf O_A, \sup O_A]$, which represents the evaluation interval value of the performance–cost ratio, equivalent to the truth-membership function of INS. $R_A = [\inf R_A, \sup R_A]$ represents the evaluation interval value of the potential risks, equivalent to the falsity-membership function of INS. $U_A = [\inf U_A, \sup U_A]$ represents the evaluation interval value of the uncertainty of P_A and R_A , equivalent to the indeterminacy-membership function of INS. A larger P_A with a smaller U_A and R_A yields a better evaluation. $O_A, R_A, U_A \in [0, 1]$, and $0 \leq \sup O_A + \sup U_A + \sup R_A \leq 3$. α, β and γ are the trade-off coefficients representing the importance degrees of the performance–cost ratio, uncertainty and potential risks, respectively, which should reflect the user's application requirements in different time periods. $\alpha, \beta, \gamma \in [0, 1]$. Obviously, CINS is also an INS.

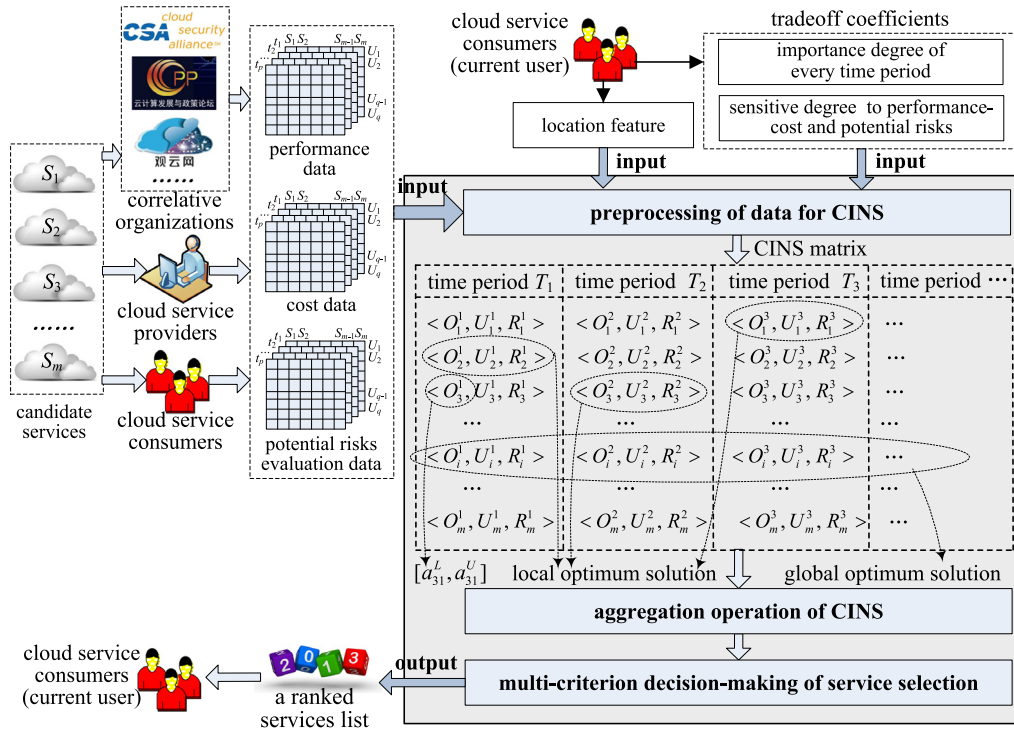


Fig. 1. Problem modeling.

Theorem 1. Let three CINSs $A = \langle \alpha_A[\inf O_A, \sup O_A], \beta_A[\inf U_A, \sup U_A], \gamma_A[\inf R_A, \sup R_A] \rangle$, $B = \langle \alpha_B[\inf O_B, \sup O_B], \beta_B[\inf U_B, \sup U_B], \gamma_B[\inf R_B, \sup R_B] \rangle$ and $C = \langle \alpha_C[\inf O_C, \sup O_C], \beta_C[\inf U_C, \sup U_C], \gamma_C[\inf R_C, \sup R_C] \rangle$, then the following equations are true.

- (1) $A \oplus B = B \oplus A$;
- (2) $A \otimes B = B \otimes A$;
- (3) $\lambda \cdot (A \oplus B) = \lambda \cdot A \oplus \lambda \cdot B, \lambda > 0$;
- (4) $(A \otimes B)^\lambda = A^\lambda \otimes B^\lambda, \lambda > 0$;
- (5) $\lambda_1 \cdot A \oplus \lambda_2 \cdot A = (\lambda_1 + \lambda_2) \otimes A, \lambda_1 > 0, \lambda_2 > 0$;
- (6) $A^{\lambda_1} \otimes A^{\lambda_2} = A^{(\lambda_1 + \lambda_2)}, \lambda_1 > 0, \lambda_2 > 0$;
- (7) $(A \oplus B) \oplus C = A \oplus (B \oplus C)$;
- (8) $(A \otimes B) \otimes C = A \otimes (B \otimes C)$.

Proof. Obviously, the proof of the above equations can be done according to Definition 6.

4. Modeling problem

4.1. Problem definition

For a list of m candidate cloud services in the set $\{S_1, S_2, \dots, S_{m-1}, S_m\}$ and a time series consisting of p timeslots $\{t_1, t_2, \dots, t_{p-1}, t_p\}$, assume that sufficient evaluation data exists about performance, cost and potential risk for every service in every timeslot. Full consideration of the geographic location feature of the current user allows these timeslots to be divided exactly into time periods in accordance with the time zone in which the current user lives. Based on an analysis of the application scenario requirements of current user, we can identify the importance degree of every time period, the sensitive degree of performance–cost ratio and the potential cloud service risks for the current user in every time period. Finally, the current user will receive a ranked list of recommended services $S_{r1} > S_{r2} > \dots > S_{r(m-1)} > S_{rm}$. The highest-ranked service in this list should

demonstrate optimal performance–costs and potential risks in the specified time periods, and it should have a higher probability than lower-ranked services of being adopted by the current user.

In this problem, every time period becomes a decision criterion for evaluating the performance–costs and potential risks of cloud services. Thus, the time-aware trustworthy cloud service selection with tradeoffs between performance–costs and potential risks over multiple time periods can be formulated as a MCDM problem of creating a ranked services list, as shown in Fig. 1.

In Fig. 1, the sources of original evaluation data about cloud services mainly includes: (1) the performance data from continuous monitoring or continuous auditing, provided by service providers; (2) the continual evaluation data about performance, cost and potential risks, provided by correlative organizations, such as CSA, 3CPP or yunzhiliang.net; (3) the feedback data about performance, cost and potential risks, provided by service consumers. By preprocessing these original data, the performance–cost evaluation and risks assessment of candidate services in every time period can be obtained. In time period T_i , the service with the optimal performance–cost and the minimal risk is the local optimum solution in the i th criterion. The challenging task is to find the global optimum solution in all of time periods.

To address this MCDM problem, all original evaluation data about performance, cost and potential risks must first be preprocessed into the CINS matrix by integrating user’s time zone information and tradeoff coefficients. After that, the CINS numbers for multiple time periods can be aggregated to compare the differences between candidate services in order to calculate the sort value of every service in ranked list of recommended services.

4.2. Preprocessing of data for CINS

The preprocessing of data for CINS consists of the following nine steps.

Step 1: Identifying the nearest neighbors for the current user. Based on the history performance evaluation data about cloud

services, employ Pearson correlation coefficient to calculate the total similarity between the current user and other user by Eq. (3):

$$\text{sim}(u^c, u^o) = \frac{1}{|S^o|} \sum_{s_i \in S^o} \text{sim}_i(u^c, u^o), \quad (3)$$

where u^c represents the current user; u^o represents other user who maybe a consumer, a service provider or a correlative organization; S^o is a union set of evaluated services by u^c and u^o ; $\text{sim}_i(u^c, u^o)$ is the similarity between u^c and u^o obtained based on service s_i as reference, which is calculated by Eq. (4):

$$\text{sim}_i(u^c, u^o) = \frac{\sum_{t \in T} (r_t^c - \bar{r}^c)(r_t^o - \bar{r}^o)}{\sqrt{\sum_{t \in T} (r_t^c - \bar{r}^c)^2} \sqrt{\sum_{t \in T} (r_t^o - \bar{r}^o)^2}}. \quad (4)$$

Then, the set of nearest neighbors of u^c , noted as NN , can be selected by Eq. (5):

$$NN = \{u^i | u^i \in SC, \text{sim}(u^c, u^i) \geq \text{sim}^{th}\} \quad (5)$$

where SC represents the set of other consumers; sim^{th} is the threshold of user similarity.

Step 2: Collecting the evaluation data about performance, cost and potential risks of candidate services from nearest neighbors. Multiple evaluation indicators of performance and potential risks may exist for different types of cloud services. For example, the performance indicators for storage services include response time, accessing rate for storage interface, efficiency of data compression, whereas the performance indicators for computational intensive services include the number of concurrent users and the efficiency of instruction execution. Taking the performance evaluation as an example, the original evaluation matrix for a cloud storage service s can be represented as follows:

$$O(s) = \begin{bmatrix} (o_{11}^1, o_{11}^2, \dots, o_{11}^r) & (o_{12}^1, o_{12}^2, \dots, o_{12}^r) & \dots & (o_{1p}^1, o_{1p}^2, \dots, o_{1p}^r) \\ (o_{21}^1, o_{21}^2, \dots, o_{21}^r) & (o_{22}^1, o_{22}^2, \dots, o_{22}^r) & \dots & (o_{2p}^1, o_{2p}^2, \dots, o_{2p}^r) \\ \vdots & \vdots & \dots & \vdots \\ (o_{q1}^1, o_{q1}^2, \dots, o_{q1}^r) & (o_{q2}^1, o_{q2}^2, \dots, o_{q2}^r) & \dots & (o_{qp}^1, o_{qp}^2, \dots, o_{qp}^r) \end{bmatrix}, \quad (6)$$

where o_{ij}^k represents the evaluation value of the k th performance indicator provided by the i th user in timeslot t_j ; p is the total number of timeslots; q is the total number of users who have evaluated this service; r is the total number of performance indicators. The potential risks of cloud services may associate multiple evaluation indicators. The multiple attributes evaluation matrix for potential risks can also be defined similarly by Eq. (6).

Step 3: Aggregating the multi-dimensional performance evaluations and risk evaluations into comprehensive evaluations with weighted arithmetic averaging operators. Because of the difference between gain-type indicators and loss-type indicators, the multi-dimensional evaluation data need to be normalized prior to aggregation operations. Gain-type indicators, such as accessing rate of storage interface and efficiency of data compression, can be normalized by Eq. (7):

$$o_{ij}^k = (o_{ij}^k - \min_{i=1}^q o_{ij}^k) / (\max_{i=1}^q o_{ij}^k - \min_{i=1}^q o_{ij}^k). \quad (7)$$

Loss-type indicators, such as response time and availability risk, are normalized by Eq. (8):

$$o_{ij}^k = (\max_{i=1}^q o_{ij}^k - o_{ij}^k) / (\max_{i=1}^q o_{ij}^k - \min_{i=1}^q o_{ij}^k). \quad (8)$$

The measurement unit of cost is usually inconsistent for different services; therefore, it should also be normalized with

the same standard. In order to aggregate the multi-attributes evaluation data, let the weights matrix be $\omega = \{\omega_1, \omega_2, \dots, \omega_r\}$. ω_i represents the weight the current user assigned to the i th attribute. The comprehensive performance evaluation of service s provided by the i th user in timeslot t_j can be determined by Eq. (9):

$$e_{ij}^p(s) = o_{ij} \cdot \omega^T = [o_{ij}^1 \ o_{ij}^2 \ \dots \ o_{ij}^r] [\omega_1 \ \omega_2 \ \dots \ \omega_r]^T. \quad (9)$$

The comprehensive evaluation of potential risks can also be defined similarly by Eq. (9).

Step 4: Calculating the performance–cost ratio of every service in every timeslot. Let e_{ij}^p and e_{ij}^c be the comprehensive performance evaluation and normalized cost, respectively, in timeslot t_j from the i th user. Then, the performance–cost ratio is defined as e_{ij}^p/e_{ij}^c .

Step 5: Dividing timeslots into time periods on the basis of analyzing the user's time zone and application requirements. Let d be the density coefficient of time period T_i , which represents the size of timeslots in T_i . Then the time period matrix is noted as follows:

$$T = \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_n \end{bmatrix} = \begin{bmatrix} t_{11} & t_{11} & \dots & t_{1d} \\ t_{21} & t_{22} & \dots & t_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ t_{n1} & t_{n2} & \dots & t_{nd} \end{bmatrix}, \quad (10)$$

where n is the number of time periods and $p = n \times d$. In practice, the density coefficient d may be a variable, because the size of time period could be different.

Step 6: Transforming the single-value evaluation data with different timeslots into interval numbers in every time period by utilizing cloud model theory. The cloud model [35,73] 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 fuzziness, randomness and uncertain concepts, and it has been applied in many fields [79,70,9]. In this paper, we establish cloud models for performance–costs and potential risks based on evaluation data in order to identify their interval numbers in every time period. Let $E_{j,k}^O(s) = \{e_{j,d \times (k-1)+1}^O, e_{j,d \times (k-1)+2}^O, \dots, e_{j,d \times k}^O\}$ be the single-value evaluation for performance–cost ratio of service s provided by the j th user in T_k . This data is viewed as cloud drops and sent into the reverse cloud generator (RCG). Then, the cloud model of performance–cost in T_i can be obtained according to Eq. (11):

$$\begin{cases} Ex_i^O = \frac{1}{d} \times \sum_{j=1}^q \sum_{k=1}^d e_{j,d \times (k-1)+k}^O \\ En_i^O = \sqrt{\frac{\pi}{2}} \times \frac{1}{q \times d} \sum_{j=1}^q \sum_{k=1}^d |e_{j,d \times (k-1)+k}^O - Ex_i^O| \\ HE_i^O = \sqrt{\left| \frac{1}{q \times d - 1} \sum_{j=1}^q \sum_{k=1}^d (e_{j,d \times (k-1)+k}^O - Ex_i^O)^2 - (En_i^O)^2 \right|}, \end{cases} \quad (11)$$

where q is the number of nearest neighbors and d is the time period's density coefficient. The service's performance–cost ratio in T_i is defined as o_i , described with an interval number as $[o_i^L, o_i^U]$. o_i^L and o_i^U are calculated with Eq. (12):

$$\begin{cases} o_i^U = Ex_i^O + En_i^O + HE_i^O \times \gamma \\ o_i^L = Ex_i^O - En_i^O - HE_i^O \times \gamma, \end{cases} \quad (12)$$

where γ is the influence coefficient of HE , suggested to remain in the interval range [0.1, 0.2] [39]. The cloud model for potential risks is established similarly, and the potential risks interval number for the service in T_i defined as $r_i = [r_i^L, r_i^U]$ is obtained

Table 1
Some typical values for tradeoff coefficients.

Importance degree of current time period	Sensitive degree	α for performance–cost	β for uncertainty	γ for potential risks
Very important	Sensitive to performance–cost	1	0.8	0.8
Very important	Quite sensitive to performance–cost	1	0.6	0.6
Important	Sensitive to performance–cost	0.8	0.6	0.6
Important	Quite sensitive to performance–cost	0.8	0.4	0.4
Very important	Sensitive to potential risks	0.8	1	1
Very important	Quite sensitive to potential risks	0.6	1	1
Important	Sensitive to potential risks	0.6	0.8	0.8
Important	Quite sensitive to potential risks	0.4	0.8	0.8
Not important	No preferences	0.5	0.5	0.5
Pay no attention	No preferences	0	0	0

with Eq. (13):

$$\begin{cases} r_i^L = Ex_i^R - En_i^R - HE_i^R \times \gamma \\ r_i^U = Ex_i^R + En_i^R + HE_i^R \times \gamma. \end{cases} \quad (13)$$

Step 7: Calculating the uncertainty interval of performance–cost ratio and potential risks in T_i . Let $\lambda_i^O = \sqrt{(En_i^O)^2 + (HE_i^O)^2}$ and $\lambda_i^R = \sqrt{(En_i^R)^2 + (HE_i^R)^2}$ be the uncertainty of performance–cost ratio and the uncertainty of potential risks, respectively, in T_i . Then, the comprehensive uncertainty interval of T_i is defined as Eq. (14):

$$U_i = [u_i^L, u_i^U] = [\min\{\lambda_i^O, \lambda_i^R\}, \max\{\lambda_i^O, \lambda_i^R\}]. \quad (14)$$

Then, the original evaluation data is noted with CINS as follows:

$$E = \begin{pmatrix} E_1 \\ E_2 \\ \vdots \\ E_m \end{pmatrix} = \begin{pmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{pmatrix} \\ = \begin{pmatrix} \langle O_{11}, U_{11}, R_{11} \rangle & \cdots & \langle O_{1n}, U_{1n}, R_{1n} \rangle \\ \vdots & \ddots & \vdots \\ \langle O_{m1}, U_{m1}, R_{m1} \rangle & \cdots & \langle O_{mn}, U_{mn}, R_{mn} \rangle \end{pmatrix}.$$

Step 8: Analyzing the user’s application scenario requirements and identifying the tradeoff coefficients α, β and γ for performance–cost, uncertainty and potential risks, respectively, in every time period. These coefficients should reflect the importance degree of every time period and the sensitive degrees of performance–cost ratio and potential risks for the cloud service. The time periods’ tradeoff coefficient is defined as

$$F = \begin{pmatrix} F_1 \\ F_2 \\ \vdots \\ F_n \end{pmatrix} = \begin{pmatrix} \alpha_1, & \beta_1, & \gamma_1 \\ \alpha_2, & \beta_2, & \gamma_2 \\ \vdots & \vdots & \vdots \\ \alpha_n, & \beta_n, & \gamma_n \end{pmatrix}, \quad (15)$$

where F_i represents the tradeoff coefficient of T_i assigned by the current user. Table 1 shows some typical values for tradeoff coefficients.

In Table 1, $\alpha, \beta, \gamma \in [0, 1]$, the current user can determine their values according to the importance of every time period and tradeoffs between performance–cost and potential risks. The fundamental principles of determining the tradeoff coefficients mainly include: (1) if the current time period is very important or has a greater importance than other time periods, $0.6 \leq \alpha, \beta, \gamma \leq 1$; (2) if the current time period is important, $0.5 \leq \alpha, \beta, \gamma \leq 0.8$; (3) if the current time period is not important, $0.1 \leq \alpha, \beta, \gamma \leq 0.5$; (4) if user pays no attention to the current time period, $\alpha = 0, \beta = 0, \gamma = 0$; (5) if user is sensitive to performance–cost, $(\alpha - \beta) \geq 0.2$ and $(\alpha - \gamma) \geq 0.2$; (6) if user is quite sensitive to performance–cost, $(\alpha - \beta) \geq 0.4$ and $(\alpha - \gamma) \geq 0.4$; (7) if user

is sensitive to potential risks, $(\beta - \alpha) \geq 0.2$ and $(\gamma - \alpha) \geq 0.2$; (8) if user is quite sensitive to potential risks, $(\beta - \alpha) \geq 0.4$ and $(\gamma - \alpha) \geq 0.4$.

Step 9: Assembling preprocessed evaluation data for candidate services in all time periods using CINS theory. According to the tradeoff coefficient F , a matrix is defined as follows:

$$Y = \begin{pmatrix} F_1 & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & F_2 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & F_3 & 0 & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \cdots & F_n \end{pmatrix} \\ = \begin{pmatrix} (\alpha_1, \beta_1, \gamma_1) & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & (\alpha_2, \beta_2, \gamma_2) & 0 & \cdots & \cdots & 0 \\ 0 & 0 & (\alpha_3, \beta_3, \gamma_3) & 0 & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & \cdots & (\alpha_n, \beta_n, \gamma_n) \end{pmatrix}.$$

Then, the comprehensive evaluation decision matrix of candidate services is given as in Box 1, where v_{ij} is a CINS representing the total evaluation of the i th service in T_i .

The most trustworthy service should have the optimal evaluation in V . In order to pick out the optimal candidate from m services in n time periods, the aggregation operators and entropy weight measure method for CINS will be designed and proved theoretically.

5. Proposed CINS aggregation methodology

5.1. Aggregation operators for CINS

Definition 8. Let $A_i = \langle \alpha_{A_i} O_{A_i}, \beta_{A_i} U_{A_i}, \gamma_{A_i} R_{A_i} \rangle$ ($i = 1, 2, \dots, n$) be a collection of CINSs. The CINSs’ aggregation operators are defined as CINSWA : $CINS^n \rightarrow CINS$,

$$CINSWA_w(A_1, A_2, \dots, A_n) \\ = w_1 \cdot A_1 \oplus w_2 \cdot A_2 \oplus \cdots \oplus w_n \cdot A_n = \sum_{i=1}^n w_i A_i, \quad (17)$$

where $W = (w_1, w_2, \dots, w_n)$ is weight vector of A_i ($i = 1, 2, \dots, n$), $w_i \geq 0$ ($i = 1, 2, \dots, n$) and $\sum_{i=1}^n w_i = 1$. CINSWA represents the CINS weighted averaging operator for the n dimension.

Theorem 2. Let $A_i = \langle \alpha_{A_i} O_{A_i}, \beta_{A_i} U_{A_i}, \gamma_{A_i} R_{A_i} \rangle$ ($i = 1, 2, \dots, n$) be a collection of CINSs, and let $W = (w_1, w_2, \dots, w_n)$ be the weight vector of A_i ($i = 1, 2, \dots, n$) with $w_i \geq 0$ ($i = 1, 2, \dots, n$) and $\sum_{i=1}^n w_i = 1$. Then, their aggregated result using CINSWA operator is also a CINS, and

$$CINSWA_w(A_1, A_2, \dots, A_n) \\ = \left\langle \left[1 - \prod_{i=1}^n (1 - \alpha_{A_i} \inf O_{A_i})^{w_i}, 1 - \prod_{i=1}^n (1 - \alpha_{A_i} \sup O_{A_i})^{w_i} \right] \right\rangle,$$

$$\begin{aligned}
 V &= \begin{pmatrix} V_1 \\ \vdots \\ V_m \end{pmatrix} = \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{pmatrix} \\
 &= E \otimes Y = \begin{pmatrix} \langle \alpha_1 O_{11}, \beta_1 U_{11}, \gamma_1 R_{11} \rangle & \cdots & \langle \alpha_n O_{1n}, \beta_n U_{1n}, \gamma_n R_{1n} \rangle \\ \vdots & \ddots & \vdots \\ \langle \alpha_1 O_{m1}, \beta_1 U_{m1}, \gamma_1 R_{m1} \rangle & \cdots & \langle \alpha_n O_{mn}, \beta_n U_{mn}, \gamma_n R_{mn} \rangle \end{pmatrix} \\
 &= \begin{pmatrix} \langle \alpha_1 [o_{11}^L, o_{11}^U], \beta_1 [u_{11}^L, u_{11}^U], \gamma_1 [r_{11}^L, r_{11}^U] \rangle & \cdots & \langle \alpha_n [o_{1n}^L, o_{1n}^U], \beta_n [u_{1n}^L, u_{1n}^U], \gamma_n [r_{1n}^L, r_{1n}^U] \rangle \\ \vdots & \ddots & \vdots \\ \langle \alpha_1 [o_{m1}^L, o_{m1}^U], \beta_1 [u_{m1}^L, u_{m1}^U], \gamma_1 [r_{m1}^L, r_{m1}^U] \rangle & \cdots & \langle \alpha_n [o_{mn}^L, o_{mn}^U], \beta_n [u_{mn}^L, u_{mn}^U], \gamma_n [r_{mn}^L, r_{mn}^U] \rangle \end{pmatrix}, \tag{16}
 \end{aligned}$$

Box I.

$$\begin{aligned}
 &\left[\prod_{i=1}^n (\beta_{A_i} \inf U_{A_i})^{w_i}, \prod_{i=1}^n (\beta_{A_i} \sup U_{A_i})^{w_i} \right], \\
 &\left[\prod_{i=1}^n (\gamma_{A_i} \inf R_{A_i})^{w_i}, \prod_{i=1}^n (\gamma_{A_i} \sup R_{A_i})^{w_i} \right] \Bigg\}, \tag{18} \\
 &\times \left[\prod_{i=1}^k (\gamma_{A_i} \inf R_{A_i})^{w_i}, \prod_{i=1}^k (\gamma_{A_i} \sup R_{A_i})^{w_i} \right] \\
 &\oplus w_{k+1} A_{k+1}
 \end{aligned}$$

and

$$\begin{aligned}
 w_{k+1} \cdot A_{k+1} &= \langle [1 - (1 - \alpha_{A_{k+1}} \inf O_{A_{k+1}})^{w_{k+1}}, \\
 &\quad 1 - (1 - \alpha_{A_{k+1}} \sup O_{A_{k+1}})^{w_{k+1}}], \\
 &\quad [(\beta_{A_{k+1}} \inf U_{A_{k+1}})^{w_{k+1}}, (\beta_{A_{k+1}} \sup U_{A_{k+1}})^{w_{k+1}}], \\
 &\quad [(\gamma_{A_{k+1}} \inf R_{A_{k+1}})^{w_{k+1}}, (\gamma_{A_{k+1}} \sup R_{A_{k+1}})^{w_{k+1}}] \rangle.
 \end{aligned}$$

Then, according to Definition 6,

$$\begin{aligned}
 CSINNWA_w(A_1, A_2, \dots, A_k, A_{k+1}) &= \left\langle \left[\left(1 - \prod_{i=1}^k (1 - \alpha_{A_i} \inf O_{A_i})^{w_i} \right) \right. \right. \\
 &\quad \left. \left. + (1 - (1 - \alpha_{A_{k+1}} \inf O_{A_{k+1}})^{w_{k+1}}) \right. \right. \\
 &\quad \left. \left. - \left(1 - \prod_{i=1}^k (1 - \alpha_{A_i} \inf O_{A_i})^{w_i} \right) \right. \right. \\
 &\quad \left. \left. \times (1 - (1 - \alpha_{A_{k+1}} \inf O_{A_{k+1}})^{w_{k+1}}) \right. \right. \\
 &\quad \left. \left. \left(1 - \prod_{i=1}^k (1 - \alpha_{A_i} \sup O_{A_i})^{w_i} \right) \right. \right. \\
 &\quad \left. \left. \times (1 - (1 - \alpha_{A_{k+1}} \sup O_{A_{k+1}})^{w_{k+1}}) \right. \right. \\
 &\quad \left. \left. - \left(1 - \prod_{i=1}^k (1 - \alpha_{A_i} \sup O_{A_i})^{w_i} \right) \right. \right. \\
 &\quad \left. \left. \times (1 - (1 - \alpha_{A_{k+1}} \sup O_{A_{k+1}})^{w_{k+1}}) \right], \right. \\
 &\quad \left[\prod_{i=1}^k (\beta_{A_i} \inf U_{A_i})^{w_i} \times ((\beta_{A_{k+1}} \inf U_{A_{k+1}})^{w_{k+1}}), \right. \\
 &\quad \left. \prod_{i=1}^k (\beta_{A_i} \sup U_{A_i})^{w_i} \times ((\beta_{A_{k+1}} \sup U_{A_{k+1}})^{w_{k+1}}) \right], \\
 &\quad \left[\prod_{i=1}^k (\gamma_{A_i} \inf R_{A_i})^{w_i} \times ((\gamma_{A_{k+1}} \inf R_{A_{k+1}})^{w_{k+1}}), \right. \\
 &\quad \left. \prod_{i=1}^k (\gamma_{A_i} \sup R_{A_i})^{w_i} \times ((\gamma_{A_{k+1}} \sup R_{A_{k+1}})^{w_{k+1}}) \right] \Bigg\} \\
 &= \left\langle \left[1 - \prod_{i=1}^{k+1} (1 - \alpha_{A_i} \inf O_{A_i})^{w_i}, 1 - \prod_{i=1}^{k+1} (1 - \alpha_{A_i} \sup O_{A_i})^{w_i} \right], \right. \\
 &\quad \left[\prod_{i=1}^{k+1} (\beta_{A_i} \inf U_{A_i})^{w_i}, \prod_{i=1}^{k+1} (\beta_{A_i} \sup U_{A_i})^{w_i} \right], \\
 &\quad \left. \left[\prod_{i=1}^{k+1} (\gamma_{A_i} \inf R_{A_i})^{w_i}, \prod_{i=1}^{k+1} (\gamma_{A_i} \sup R_{A_i})^{w_i} \right] \right\rangle,
 \end{aligned}$$

where $w_i \in [0, 1]$ and $\sum_{i=1}^n w_i = 1$.

Proof. Eq. (18) can be proven by means of mathematical induction.

When $n = 2$, then $CINSWA_w(A_1, A_2) = w_1 \cdot A_1 \oplus w_2 \cdot A_2$. According to Definition 6, $w_1 \cdot A_1 = \langle [1 - (1 - \alpha_{A_1} \inf O_{A_1})^{w_1}, 1 - (1 - \alpha_{A_1} \sup O_{A_1})^{w_1}], [(\beta_{A_1} \inf U_{A_1})^{w_1}, (\beta_{A_1} \sup U_{A_1})^{w_1}], [(\gamma_{A_1} \inf R_{A_1})^{w_1}, (\gamma_{A_1} \sup R_{A_1})^{w_1}] \rangle$ and $w_2 \cdot A_2 = \langle [1 - (1 - \alpha_{A_2} \inf O_{A_2})^{w_2}, 1 - (1 - \alpha_{A_2} \sup O_{A_2})^{w_2}], [(\beta_{A_2} \inf U_{A_2})^{w_2}, (\beta_{A_2} \sup U_{A_2})^{w_2}], [(\gamma_{A_2} \inf R_{A_2})^{w_2}, (\gamma_{A_2} \sup R_{A_2})^{w_2}] \rangle$. Then,

$$\begin{aligned}
 w_1 \cdot A_1 \oplus w_2 \cdot A_2 &= \langle [(1 - (1 - \alpha_{A_1} \inf O_{A_1})^{w_1}) + (1 - (1 - \alpha_{A_2} \inf O_{A_2})^{w_2}) \\
 &\quad - (1 - (1 - \alpha_{A_1} \inf O_{A_1})^{w_1}) \times (1 - (1 - \alpha_{A_2} \inf O_{A_2})^{w_2}), \\
 &\quad (1 - (1 - \alpha_{A_1} \sup O_{A_1})^{w_1}) + (1 - (1 - \alpha_{A_2} \sup O_{A_2})^{w_2}) \\
 &\quad - (1 - (1 - \alpha_{A_1} \sup O_{A_1})^{w_1}) \times (1 - (1 - \alpha_{A_2} \sup O_{A_2})^{w_2}), \\
 &\quad [(\beta_{A_1} \sup U_{A_1})^{w_1} \cdot (\beta_{A_2} \inf U_{A_2})^{w_2}, (\beta_{A_1} \sup U_{A_1})^{w_1} \\
 &\quad \times (\beta_{A_2} \sup U_{A_2})^{w_2}], \\
 &\quad [(\gamma_{A_1} \inf R_{A_1})^{w_1} \times (\gamma_{A_2} \inf R_{A_2})^{w_2}, (\gamma_{A_1} \sup R_{A_1})^{w_1} \\
 &\quad \times (\gamma_{A_2} \sup R_{A_2})^{w_2}] \rangle \\
 &= \left\langle \left[1 - \prod_{i=1}^2 (1 - \alpha_{A_i} \inf O_{A_i})^{w_i}, 1 - \prod_{i=1}^2 (1 - \alpha_{A_i} \sup O_{A_i})^{w_i} \right], \right. \\
 &\quad \left[\prod_{i=1}^2 (\beta_{A_i} \inf U_{A_i})^{w_i}, \prod_{i=1}^2 (\beta_{A_i} \sup U_{A_i})^{w_i} \right], \\
 &\quad \left. \left[\prod_{i=1}^2 (\gamma_{A_i} \inf R_{A_i})^{w_i}, \prod_{i=1}^2 (\gamma_{A_i} \sup R_{A_i})^{w_i} \right] \right\rangle.
 \end{aligned}$$

Thus, the equation holds.

Assume that the equation holds when $n = k$. Then when $n = k + 1$,

$$\begin{aligned}
 CSINNWA_w(A_1, A_2, \dots, A_k, A_{k+1}) &= (w_1 \cdot A_1 \oplus w_2 \cdot A_2 \oplus \dots \oplus w_k \cdot A_k) \oplus w_{k+1} \cdot A_{k+1} \\
 &= \left\langle \left[1 - \prod_{i=1}^k (1 - \alpha_{A_i} \inf O_{A_i})^{w_i}, 1 - \prod_{i=1}^k (1 - \alpha_{A_i} \sup O_{A_i})^{w_i} \right], \right. \\
 &\quad \left. \times \left[\prod_{i=1}^k (\beta_{A_i} \inf U_{A_i})^{w_i}, \prod_{i=1}^k (\beta_{A_i} \sup U_{A_i})^{w_i} \right], \right.
 \end{aligned}$$

$$\left[\prod_{i=1}^{k+1} (\gamma_{A_i} \inf R_{A_i})^{w_i}, \prod_{i=1}^{k+1} (\gamma_{A_i} \sup R_{A_i})^{w_i} \right].$$

Considering the above results, Eq. (18) holds for any n . This completes the proof.

The CINSWA operator has the following properties:

- (1) Idempotency: Let A_i ($i = 1, 2, \dots, n$) be a collection of CINSs. If all A_i ($i = 1, 2, \dots, n$) are equal, that is, $A_i = A$, for all $i \in \{1, 2, \dots, n\}$, then $CINSWA_w(A_1, A_2, \dots, A_n) = A$.
- (2) Boundedness: Assume A_i ($i = 1, 2, \dots, n$) is a collection of CINSs, and A^U and A^L are defined as follows:

$$\begin{aligned} A^U &= \left\langle \max_{i=1}^n \{\alpha_{A_i} O_{A_i}(x)\}, \min_{i=1}^n \{\beta_{A_i} U_{A_i}(x)\}, \min_{i=1}^n \{\gamma_{A_i} R_{A_i}(x)\} \right\rangle \\ &= \left\langle \max_{i=1}^n \{\alpha_{A_i} [\inf O_{A_i}(x), \sup O_{A_i}(x)]\}, \min_{i=1}^n \{\beta_{A_i} [\inf U_{A_i}(x), \sup U_{A_i}(x)]\}, \min_{i=1}^n \{\gamma_{A_i} [\inf R_{A_i}(x), \sup R_{A_i}(x)]\} \right\rangle, \\ A^L &= \left\langle \min_{i=1}^n \{\alpha_{A_i} O_{A_i}(x)\}, \max_{i=1}^n \{\beta_{A_i} U_{A_i}(x)\}, \max_{i=1}^n \{\gamma_{A_i} R_{A_i}(x)\} \right\rangle \\ &= \left\langle \min_{i=1}^n \{\alpha_{A_i} [\inf O_{A_i}(x), \sup O_{A_i}(x)]\}, \max_{i=1}^n \{\beta_{A_i} [\inf U_{A_i}(x), \sup U_{A_i}(x)]\}, \max_{i=1}^n \{\gamma_{A_i} [\inf R_{A_i}(x), \sup R_{A_i}(x)]\} \right\rangle. \end{aligned}$$

The comparison operation between interval numbers can be executed using Eq. (1). Based on the possibility degree matrix, the sort value of each interval number can be calculated by Eq. (2). For all $i \in \{1, 2, \dots, n\}$, $A^L \in CINSWA_w(A_1, A_2, \dots, A_n) \in A^U$.

- (3) Monotonicity: Assuming A_i ($i = 1, 2, \dots, n$) is a collection of CINSs, if $A_i \subseteq A_i^*$ and $i \in \{1, 2, \dots, n\}$, then $CINSWA_w(A_1, A_2, \dots, A_n) \in CINSWA_w(A_1^*, A_2^*, \dots, A_n^*)$.

5.2. Entropy weight measure for CINS

In information theory, entropy is a measure for calculating the uncertainty associated with a random variable. Therefore, it is reasonable to utilize entropy as a vehicle to obtain objective weight [74]. According to entropy theory, if a decision criterion in a MCDM problem provides more uncertainty than others, it may be paid more attention. The entropy weight measure for CINSs is defined based on the axiomatic definition of the entropy measure for single-valued neutrosophic sets [41], in order to calculate the weights of time periods.

Definition 9. The entropy on CINS(X) is a real function $E : CINS(X) \rightarrow [0, 1]$ if E satisfies the following properties:

- (P1) $E(A) = 0$ if the cloud service associated with A is totally trustworthy;
- (P2) $E(A) = 1$ if the cloud service associated with A is totally untrusted.

Definition 10. Let A be a CINS in the universal discourse $X = \{x_1, x_2, \dots, x_n\}$. $E(A)$ is a measure such that

$$E(A) = 1 - d(A, A^+), \tag{19}$$

where $d(A, A^+)$ refers to the distance measure between CINS A and positive ideal CINS A^+ . $A^+ = \langle [\inf P_{A^+}, \sup P_{A^+}], [\inf U_{A^+}, \sup U_{A^+}], [\inf R_{A^+}, \sup R_{A^+}] \rangle = \langle [1, 1], [0, 0], [0, 0] \rangle$.

Definition 11 ([76]). Let A and B be two CINSs in the universal discourse $X = \{x_1, x_2, \dots, x_m\}$. Then, the Euclidean distance between them is calculated with Eq. (20):

$$\begin{aligned} d(A, A^+) &= \frac{1}{6} \left[(\alpha_A \inf O_{A(x_i)} - \inf O_{A^+})^2 + (\alpha_A \sup O_{A(x_i)} - \sup O_{A^+})^2 \right. \\ &\quad + (\beta_A \inf U_{A(x_i)} - \inf U_{A^+})^2 + (\beta_A \sup U_{A(x_i)} - \sup U_{A^+})^2 \\ &\quad \left. + (\gamma_A \inf R_{A(x_i)} - \inf R_{A^+})^2 + (\gamma_A \sup R_{A(x_i)} - \sup R_{A^+})^2 \right]^{1/2}. \end{aligned} \tag{20}$$

Theorem 3. The proposed measure $E(A)$ satisfies all the axioms given in Definition 9.

Proof. Let $A = \langle \alpha_A [\inf O_A, \sup O_A], \beta_A [\inf U_A, \sup U_A], \gamma_A [\inf R_A, \sup R_A] \rangle$ be a CINS, and $A^+ = \langle [\inf P_{A^+}, \sup P_{A^+}], [\inf U_{A^+}, \sup U_{A^+}], [\inf R_{A^+}, \sup R_{A^+}] \rangle = \langle [1, 1], [0, 0], [0, 0] \rangle$.

- (P1) If the cloud service associated with A is totally trustworthy, $\alpha_A \inf O_A = \alpha_A \sup O_A = 1, \beta_A \inf U_A = \beta_A \sup U_A = 0, \gamma_A \inf R_A = \gamma_A \sup R_A = 0$. Then, A is a positive ideal CINS, $A = \langle [1, 1], [0, 0], [0, 0] \rangle$. Therefore, $E(A) = 0$, and (P1) in Definition 9 holds.
- (P2) If the cloud service associated with A is totally untrusted, $\alpha_A \inf O_A = \alpha_A \sup O_A = 0, \beta_A \inf U_A = \beta_A \sup U_A = 1, \gamma_A \inf R_A = \gamma_A \sup R_A = 1$. Then, A is a negative ideal CINS, $A = \langle [0, 0], [1, 1], [1, 1] \rangle$. Therefore, $E(A) = 1$, and (P2) in Definition 9 holds.

Definition 12. Let CINS v_{ij} be the comprehensive evaluation of the i th service in the j th time period in V defined by Eq. (16). The entropy of the j th time period is obtained by the average entropy distance between any two v_{ij} in this time period, which is noted as follows:

$$E(T_j) = 1 - \frac{2}{m(m-1)} \sum_{i=1}^m \sum_{k=i+1}^m |E(v_{ij}) - E(v_{kj})|, \tag{21}$$

where $E(v_{ij})$ is calculated by Eq. (19).

According to these theories, an entropy weight measure is established to determine the weight of every time period under the CINS environment:

$$W(T_i) = (1 - E(T_i)) / \left(n - \sum_{i=1}^n E(T_i) \right). \tag{22}$$

Property 1. The proposed weight measure satisfies the following properties:

- (P1) $W(T_i) \in [0, 1]$;
- (P2) $\sum_{i=1}^n W(T_i) = 1$.

Proof. (P1) Let $W = (W(T_1), W(T_2), \dots, W(T_n))$ be an entropy weight vector calculated according to Eq. (22). According to Theorem 3, the entropy value of CINS lies between 0 and 1, that is, $E(v_{ij}) \in [0, 1]$; therefore, $|E(v_{ij}) - E(v_{kj})| \in [0, 1]$, the average entropy distance between any two v_{ij} , namely,

$$\frac{2}{m(m-1)} \sum_{i=1}^m \sum_{k=i+1}^m |E(v_{ij}) - E(v_{kj})| \in [0, 1],$$

and $1 - E(T_i) \in [0, 1]$. Additionally,

$$(1 - E(T_i)) + \left(n - 1 + \sum_{i=1, i \neq j}^n E(T_i) \right) = n - \sum_{i=1}^n E(T_i) \geq 0$$

and

$$\left(n - 1 + \sum_{i=1, i \neq j}^n E(T_i) \right) \geq 0$$

hold, which means that

$$n - \sum_{i=1}^n E(T_i) \geq (1 - E(T_i))$$

is true. Based on these conclusions, it is possible to obtain

$$W(T_i) = \frac{1 - E(T_i)}{n - \sum_{i=1}^n E(T_i)} \in [0, 1].$$

(P2) It is obvious that

$$\begin{aligned} \sum_{i=1}^n W(T_i) &= \sum_{i=1}^n \frac{1 - E(T_i)}{n - \sum_{j=1}^n E(T_j)} \\ &= \frac{\sum_{i=1}^n (1 - E(T_i))}{n - \sum_{j=1}^n E(T_j)} = \frac{n - \sum_{i=1}^n E(T_i)}{n - \sum_{j=1}^n E(T_j)} = 1. \end{aligned}$$

Therefore, [Property 1](#) holds.

In particular, [Table 1](#) states that if the current users pay no attention to the i th time period, then $\alpha_i = \beta_i = \gamma_i = 0$. In this case, every v_{ij} in the i th time period will be substituted with the negative ideal CINS, which will ensure $W(T_i) = 0$ in the entropy weight measure.

6. MCDM procedure for time-aware trustworthy service selection

Assume there are m cloud services $S = \{S_1, S_2, \dots, S_m\}$ and n time periods $T = \{T_1, T_2, \dots, T_n\}$. Let $V = (v_{ij})_{m \times n}$ be the comprehensive evaluation decision matrix, where $v_{ij} = \langle \alpha_j O_{ij}, \beta_j U_{ij}, \gamma_j R_{ij} \rangle$ is an evaluation value denoted by CINS. The following paragraphs propose the MCDM procedure that considers the integrated weights in order to rank and select the most trustworthy cloud service.

Step 1. Calculating the entropy value of the set $V = \{v_{ij}\}$. Using [Eq. \(19\)](#), the entropy value matrix of V can be calculated as follows:

$$\begin{aligned} E(V) &= \begin{bmatrix} E(v_{11}) & E(v_{12}) & \cdots & E(v_{1n}) \\ E(v_{21}) & E(v_{22}) & \cdots & E(v_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ E(v_{m1}) & E(v_{m2}) & \cdots & E(v_{mn}) \end{bmatrix} \\ &= \begin{bmatrix} 1 - d(v_{11}, A^+) & 1 - d(v_{12}, A^+) & \cdots & 1 - d(v_{1n}, A^+) \\ 1 - d(v_{21}, A^+) & 1 - d(v_{22}, A^+) & \cdots & 1 - d(v_{2n}, A^+) \\ \vdots & \vdots & \ddots & \vdots \\ 1 - d(v_{m1}, A^+) & 1 - d(v_{m2}, A^+) & \cdots & 1 - d(v_{mn}, A^+) \end{bmatrix}. \end{aligned}$$

Step 2. Calculating the objective weight matrix of the time periods. The entropy of the time periods must first be calculated as follows:

$$\begin{aligned} E(T) &= \begin{bmatrix} E(T_1) \\ E(T_2) \\ \vdots \\ E(T_n) \end{bmatrix} \\ &= \begin{bmatrix} 1 - \frac{2}{m(m-1)} \sum_{i=1}^m \sum_{k=i+1}^m |E(v_{i1}) - E(v_{k1})| \\ 1 - \frac{2}{m(m-1)} \sum_{i=1}^m \sum_{k=i+1}^m |E(v_{i2}) - E(v_{k2})| \\ \vdots \\ 1 - \frac{2}{m(m-1)} \sum_{i=1}^m \sum_{k=i+1}^m |E(v_{in}) - E(v_{kn})| \end{bmatrix}. \end{aligned}$$

[Eq. \(22\)](#) can easily calculate the objective weight matrix of the time periods:

$$W(T) = \begin{bmatrix} W(T_1) \\ W(T_2) \\ \vdots \\ W(T_n) \end{bmatrix} = \begin{bmatrix} (1 - E(T_1)) / \left(n - \sum_{i=1}^n E(T_i) \right) \\ (1 - E(T_2)) / \left(n - \sum_{i=1}^n E(T_i) \right) \\ \vdots \\ (1 - E(T_n)) / \left(n - \sum_{i=1}^n E(T_i) \right) \end{bmatrix}.$$

Step 3. Using CINSWA operator to obtain CINS y_i for service S_i as follows:

$$y_i = \text{CINSWA}_w(v_{i1}, v_{i2}, \dots, v_{in}). \tag{23}$$

Step 4. Calculating the sort value of every candidate service. Inspired by the TOPSIS method [\[30\]](#), define a positive ideal CINS A^+ and a negative ideal CINS A^- as follows:

$$\begin{aligned} A^+ &= \langle O_{A^+}, U_{A^+}, R_{A^+} \rangle \\ &= \langle \max_{i=1}^n \{\alpha_{y_i} O_{y_i}\}, \min_{i=1}^n \{\beta_{y_i} U_{y_i}\}, \min_{i=1}^n \{\gamma_{y_i} R_{y_i}\} \rangle; \\ A^- &= \langle O_{A^-}, U_{A^-}, R_{A^-} \rangle \\ &= \langle \min_{i=1}^n \{\alpha_{y_i} O_{y_i}\}, \max_{i=1}^n \{\beta_{y_i} U_{y_i}\}, \max_{i=1}^n \{\gamma_{y_i} R_{y_i}\} \rangle. \end{aligned}$$

Then, the Hamming distances between service S_i and ideal CINSs A^+ and A^- can be obtained using [Eqs. \(24\)](#) and [\(25\)](#):

$$\begin{aligned} d^+(y_i, A^+) &= 1 - \left[\frac{1}{6} (|\alpha_{y_i} \inf O_{y_i} - \inf O_{A^+}| + |\alpha_{y_i} \sup O_{y_i} - \sup O_{A^+}|) \right. \\ &\quad + |\beta_{y_i} \inf U_{y_i} - \inf U_{A^+}| + |\beta_{y_i} \sup U_{y_i} - \sup U_{A^+}| \\ &\quad \left. + |\gamma_{y_i} \inf R_{y_i} - \inf R_{A^+}| + |\gamma_{y_i} \sup R_{y_i} - \sup R_{A^+}| \right], \end{aligned} \tag{24}$$

$$\begin{aligned} d^-(y_i, A^-) &= 1 - \left[\frac{1}{6} (|\alpha_{y_i} \inf O_{y_i} - \inf O_{A^-}| + |\alpha_{y_i} \sup O_{y_i} - \sup O_{A^-}|) \right. \\ &\quad + |\beta_{y_i} \inf U_{y_i} - \inf U_{A^-}| + |\beta_{y_i} \sup U_{y_i} - \sup U_{A^-}| \\ &\quad \left. + |\gamma_{y_i} \inf R_{y_i} - \inf R_{A^-}| + |\gamma_{y_i} \sup R_{y_i} - \sup R_{A^-}| \right]. \end{aligned} \tag{25}$$

Calculate the sort value of every candidate service according to [Eq. \(26\)](#):

$$f_i^* = d^-(y_i, A^-) / (d^+(y_i, A^+) + d^-(y_i, A^-)). \tag{26}$$

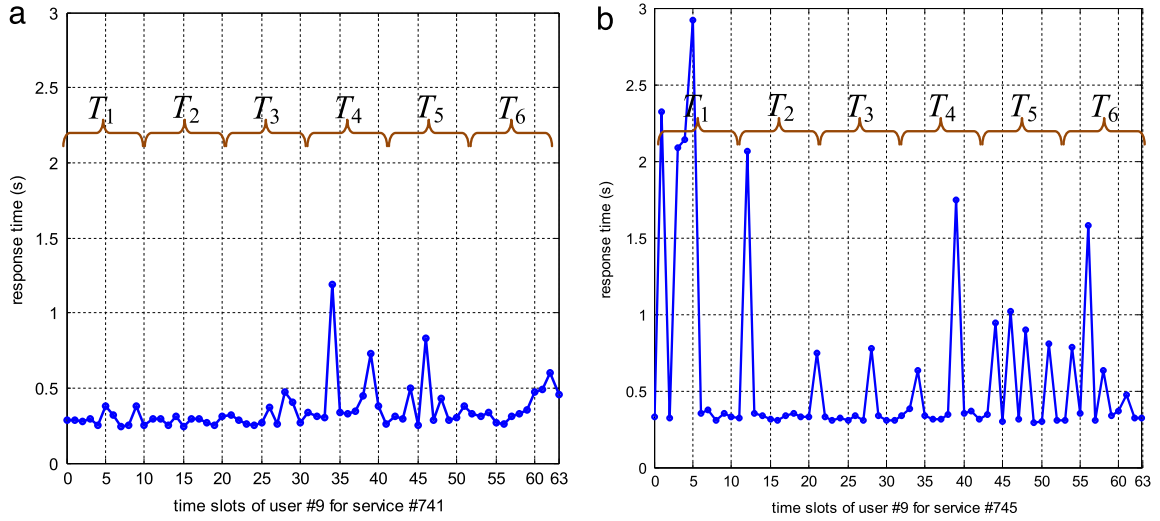


Fig. 2. Time period feature of response time. (a) service #741; (b) service #745.

Step 5. Obtaining the priority of service S_i in accordance with f_i^* and rank the candidate services. Then, the ranked list of services $S_{r_1} > S_{r_2} > \dots > S_{r_{m-1}} > S_{r_m}$ will be recommended to the current user. The highest-ranked service in this list will have the optimal performance–costs and potential risks in n time periods, and it will have a higher probability than lower-ranked services of being adopted by the current user.

7. Experiments

In order to demonstrate our approach in experiments, we used WS-DREAM dataset #3 [11,86], which collected real-world QoS evaluations from PlanetLab [50], including response time and throughput, from 142 users on 4,532 services in 64 different timeslots. WS-DREAM datasets have been applied in much research concerned with cloud computing [88,16,87]. The analysis of response times, shown in Fig. 2, illustrates the fact that the services perform differently in six time periods. According to Fig. 2, user #9 experienced a different QoS for service #741 with service #745. Service #741 provided good performance in six time periods, whereas the performance of service #745 was unsatisfactory in time periods T_1 and T_2 .

Moreover, the coefficients of variation for response times of 3,873 services are larger than 1.0, as shown in Fig. 3. The main reasons behind this finding are significant differences of client features among users, unpredictable network congestion and unexpected exceptions.

In the following experiments, let us consider a list of $m = 8$ candidate services S_1, S_2, \dots, S_8 with time periods $n = 6$. Taking services #741 through #748 as an example, we employ the original evaluation data for response time in three numerical examples to demonstrate the proposed approach. The original data used in the experiments is provided online [24].

In order to measure the accuracy of our approach, the real response time experienced by current user is employed as an appropriate baseline for comparative analysis. The baseline sort

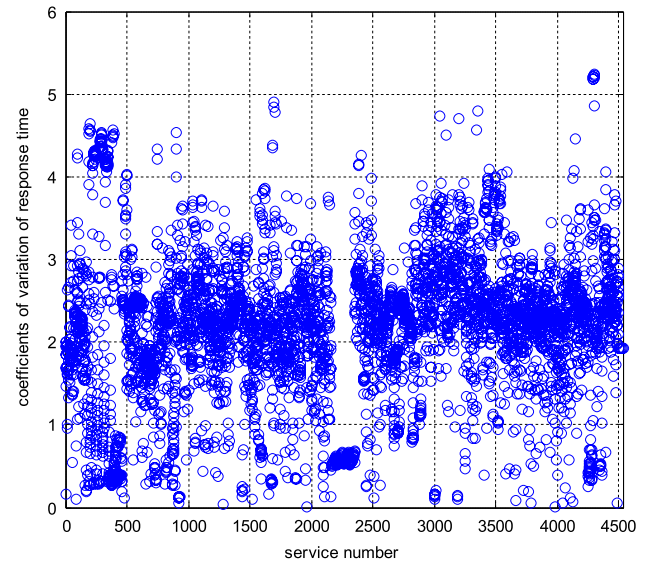


Fig. 3. Distribution of coefficients of variation for response times.

value of service S_i ($i = 1, 2, \dots, m$), noted as f_i^b , can be obtained by Eq. (27):

$$f_i^b = \frac{|risk_i^b - risk_i^{b-}|}{|perf_i^b - perf_i^{b+}| + |risk_i^b - risk_i^{b-}|}, \quad (27)$$

where f_i^b is the baseline sort value of S_i ; $perf_i^b = \sum_{j=1}^n (\alpha_j \times \sum_{k=(j-1) \times d+1}^{j \times d} perf_k) / \sum_{j=1}^n \alpha_j$ and $risk_i^b = \sum_{j=1}^n (\gamma_j \times \sum_{k=(j-1) \times d+1}^{j \times d} risk_k) / \sum_{j=1}^n \gamma_j$ represent the total response time and the total risk value of S_i aggregated with weights in all of time periods, respectively; α_j and γ_j are the tradeoff coefficients for performance–cost and risks respectively in T_j ; $perf_k$ and $risk_k$ represent the actual response time and risk value experienced by the current user in the k th timeslot; $risk_i^{b-} = \max_{i=1}^n \{risk_i^b\}$, $perf_i^{b+} = \max_{i=1}^n \{perf_i^b\}$. The order of S_i in baseline ranking can be obtained in accordance with

Table 2
Parameters of time periods in WS-DREAM.

Time periods	T_1	T_2	T_3	T_4	T_5	T_6
Range of timeslots	[0, 10]	[11, 20]	[21, 30]	[31, 40]	[41, 51]	[52, 63]
Line number ranges	[1, 1139]	[1140, 2146]	[2147, 3135]	[3136, 4105]	[4106, 5159]	[5160, 6294]

Table 3
Performance cloud models of candidate services.

Time periods	T ₁			T ₂			T ₃			T ₄			T ₅			T ₆		
	Ex	En	HE	Ex	En	HE	Ex	En	HE	Ex	En	HE	Ex	En	HE	Ex	En	HE
Cloud model of service #1	0.7042	0.8228	1.1786	0.7473	0.8903	1.2059	0.7582	0.8997	1.2174	1.0673	1.5436	2.0819	1.1396	1.6722	1.9725	1.0898	1.5742	2.2096
Cloud model of service #2	0.2435	0.1899	0.2299	0.3006	0.3013	0.3473	0.2655	0.2269	0.3207	0.3865	0.4664	0.6919	0.5847	0.8976	1.5831	0.3113	0.2715	0.3615
Cloud model of service #3	0.3389	0.3934	0.7359	0.2878	0.2773	0.5341	0.2694	0.2346	0.3383	0.3140	0.3097	0.4255	0.3412	0.3442	0.4518	0.5299	0.7322	0.9109
Cloud model of service #4	8.1203	9.1182	5.2685	5.6057	8.4542	4.5138	0.5502	0.7204	0.9895	0.8781	1.4457	2.0209	1.0223	1.7779	2.2971	0.9100	1.4903	1.8239
Cloud model of service #5	0.8710	1.1218	1.2106	0.9058	1.1919	1.5969	0.8374	1.0518	1.0938	1.1646	1.7221	2.0135	1.1453	1.7599	1.9768	0.5996	0.6256	0.4153
Cloud model of service #6	0.8512	1.0289	1.6780	0.7020	0.6822	1.0815	0.7113	0.7296	1.1174	0.8925	1.1360	1.4620	1.1501	1.6507	2.0436	1.0891	1.6104	2.2921
Cloud model of service #7	0.4009	0.5304	1.5586	0.2769	0.2622	0.4691	0.2676	0.2392	0.4431	0.4259	0.6008	1.6537	0.6526	1.1206	2.2854	0.4675	0.7077	1.3949
Cloud model of service #8	0.4392	0.6203	1.6430	0.2623	0.2383	0.4598	0.2688	0.2465	0.4701	0.3066	0.3332	0.5933	0.3630	0.4599	0.5849	0.3546	0.4446	0.5920

Table 4
Potential risk cloud models of candidate services.

Time periods	T ₁			T ₂			T ₃			T ₄			T ₅			T ₆		
	Ex	En	HE	Ex	En	HE	Ex	En	HE	Ex	En	HE	Ex	En	HE	Ex	En	HE
Cloud model of service #1	0.0273	0.0640	0.1172	0.0306	0.0708	0.1182	0.0325	0.0762	0.1186	0.0567	0.1304	0.1705	0.0688	0.1591	0.1888	0.0561	0.1306	0.1737
Cloud model of service #2	0.0000	0.0000	0.0000	0.0012	0.0029	0.0074	0.0007	0.0017	0.0057	0.0108	0.0256	0.0525	0.0244	0.0568	0.1013	0.0016	0.0039	0.0111
Cloud model of service #3	0.0095	0.0235	0.0656	0.0052	0.0128	0.0415	0.0012	0.0029	0.0081	0.0035	0.0084	0.0173	0.0037	0.0090	0.0211	0.0186	0.0438	0.0884
Cloud model of service #4	0.5235	0.6083	0.3584	0.3562	0.5669	0.3090	0.0231	0.0543	0.0881	0.0496	0.1136	0.1545	0.0640	0.1480	0.1862	0.0580	0.1333	0.1725
Cloud model of service #5	0.0288	0.0638	0.1099	0.0358	0.0819	0.1487	0.0272	0.0602	0.1005	0.0567	0.1262	0.1681	0.0665	0.1511	0.1934	0.0074	0.0174	0.0333
Cloud model of service #6	0.0295	0.0690	0.1113	0.0216	0.0518	0.1100	0.0229	0.0542	0.1109	0.0420	0.0962	0.1482	0.0620	0.1430	0.1849	0.0562	0.1316	0.1770
Cloud model of service #7	0.0084	0.0204	0.0790	0.0040	0.0099	0.0281	0.0037	0.0091	0.0265	0.0120	0.0292	0.0857	0.0243	0.0570	0.1285	0.0178	0.0422	0.0887
Cloud model of service #8	0.0124	0.0305	0.0990	0.0037	0.0090	0.0300	0.0043	0.0106	0.0300	0.0068	0.0166	0.0455	0.0085	0.0201	0.0337	0.0090	0.0216	0.0349

Table 5
Preprocessed evaluation data with same service cost expressed by CINS.

E	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																			
E ₁	0.91	1.00	0.13	1.00	0.00	0.10	0.88	1.00	0.14	1.00	0.00	0.11	0.11	1.00	0.14	1.00	0.00	0.12	0.09	1.00	0.21	1.00	0.00	0.20	0.03	1.00	0.25	1.00	0.00	0.25	0.01	1.00	0.22	1.00	0.00	0.20	
E ₂	0.97	1.00	0.00	0.30	0.00	0.00	0.96	1.00	0.01	0.46	0.00	0.00	0.74	1.00	0.01	0.39	0.00	0.00	0.70	1.00	0.06	0.83	0.00	0.04	0.47	1.00	0.12	1.00	0.00	0.09	0.79	1.00	0.01	0.45	0.00	0.01	
E ₃	0.95	1.00	0.07	0.83	0.00	0.04	0.96	1.00	0.04	0.60	0.00	0.02	0.73	1.00	0.01	0.41	0.00	0.00	0.78	1.00	0.02	0.53	0.00	0.01	0.76	1.00	0.02	0.57	0.00	0.01	0.54	1.00	0.10	1.00	0.00	0.07	
E ₄	0.00	1.00	0.71	1.00	0.00	1.00	0.00	1.00	0.65	1.00	0.00	0.95	0.31	1.00	0.10	1.00	0.00	0.09	0.18	1.00	0.19	1.00	0.00	0.18	0.02	1.00	0.24	1.00	0.00	0.23	0.12	1.00	0.22	1.00	0.00	0.21	
E ₅	0.88	1.00	0.13	1.00	0.00	0.10	0.84	1.00	0.17	1.00	0.00	0.13	0.00	1.00	0.12	1.00	0.00	0.10	0.00	0.20	1.00	0.21	1.00	0.00	0.20	0.00	1.00	0.25	1.00	0.00	0.24	0.57	1.00	0.04	0.75	0.00	0.03
E ₆	0.88	1.00	0.13	1.00	0.00	0.11	0.90	1.00	0.12	1.00	0.00	0.08	0.22	1.00	0.12	1.00	0.00	0.09	0.30	1.00	0.18	1.00	0.00	0.15	0.03	1.00	0.23	1.00	0.00	0.22	0.00	1.00	0.22	1.00	0.00	0.21	
E ₇	0.94	1.00	0.08	1.00	0.00	0.04	0.96	1.00	0.03	0.54	0.00	0.02	0.72	1.00	0.03	0.50	0.00	0.02	0.61	1.00	0.09	1.00	0.09	1.00	0.00	0.05	1.00	0.14	1.00	0.00	0.09	0.55	1.00	0.10	1.00	0.00	0.07
E ₈	0.93	1.00	0.10	1.00	0.00	0.05	0.96	1.00	0.03	0.52	0.00	0.02	0.72	1.00	0.03	0.53	0.00	0.02	0.77	1.00	0.05	0.68	0.00	0.03	0.72	1.00	0.04	0.74	0.00	0.03	0.71	1.00	0.04	0.74	0.00	0.03	

Table 6
Preprocessed evaluation data of service #1 with discounts expressed by CINS.

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	0.13	1.00	0.00	0.10	0.98	1.00	0.14	1.00	0.00	0.11	0.12	1.00	0.14	1.00	0.00	0.12	0.10	1.00	0.21	1.00	0.00	0.20	0.03	1.00	0.25	1.00	0.00	0.25	0.02	1.00	0.22	1.00	0.00	0.20	
20%	1.00	1.00	0.13	1.00	0.00	0.10	1.00	0.14	1.00	0.00	0.11	0.14	1.00	0.14	1.00	0.14	1.00	0.00	0.12	0.11	1.00	0.21	1.00	0.00	0.20	0.04	1.00	0.25	1.00	0.00	0.25	0.02	1.00	0.22	1.00	0.00	0.20
30%	1.00	1.00	0.13	1.00	0.00	0.10	1.00	0.14	1.00	0.00	0.11	0.16	1.00	0.14	1.00	0.14	1.00	0.00	0.12	0.12	1.00	0.21	1.00	0.00	0.20	0.04	1.00	0.25	1.00	0.00	0.25	0.02	1.00	0.22	1.00	0.00	0.20
40%	1.00	1.00	0.13	1.00	0.00	0.10	1.00	0.14	1.00	0.00	0.11	0.18	1.00	0.14	1.00	0.14	1.00	0.00	0.12	0.15	1.00	0.21	1.00	0.00	0.20	0.05	1.00	0.25	1.00	0.00	0.25	0.02	1.00	0.22	1.00	0.00	0.20
50%	1.00	1.00	0.13	1.00	0.00	0.10	1.00	0.14	1.00	0.00	0.11	0.22	1.00	0.14	1.00	0.14	1.00	0.00	0.12	0.17	1.00	0.21	1.00	0.00	0.20	0.06	1.00	0.25	1.00	0.00	0.25	0.03	1.00	0.22	1.00	0.00	0.20

f_i^b . The difference degree, noted as D , is defined to compare our ranked service list and the baseline list as follows:

$$D = \sum_{i=1}^m |d_i| = \sum_{i=1}^m \frac{|R_i - B_i|}{B_i}, \quad (28)$$

where R_i represents the ranking order of S_i obtained by our approach; B_i represents the order of S_i in baseline ranking; d_i represents the relative difference of S_i . Obviously, smaller D means better accuracy.

7.1. Preprocessing evaluation data

The original data is divided into six time periods. Table 2 shows the range of timeslots and the line number ranges in datasets for every time period.

Targeting response time, we evaluate the potential risks of services with Eq. (29):

$$v_i^t = \begin{cases} 0, & rt_i < \zeta \\ (\delta \times (rt_i - \zeta)) / \zeta, & \zeta \leq rt_i \leq (\zeta(1 + \delta)) / \delta \\ 1, & (\zeta(1 + \delta)) / \delta < rt_i, \end{cases} \quad (29)$$

where ζ is the user's expectation of response time and rt_i represents the response time experienced by user i . If $rt_i \leq \zeta$, the i th user considers this service to be risk-free. δ is an adjustment factor that determines the tolerable range for response time. According to the "2–5–10" principle [14] of response time in software testing analysis, we can set $\zeta = 2s$ and $\delta = 0.25$. In addition, γ is set as 0.1.

In experiments, user #9 is viewed as the current user. Assume service #740 is in S^o and the nearest neighbors of user #9 are identified with $sim^{th} = 0.2$. Then, on the basis of evaluation data from nearest neighbors, the cloud models of performance and potential risks of candidate services can be obtained according to Eqs. (11)–(13), shown in Tables 3 and 4. The original evaluation data can be transformed into CINS, as shown in Table 5.

Because no cost data exists for services in the dataset, assume that the costs of all services are identical. Considering that in the MCDM procedure, the cost of services plays a part with the performance of services together, namely performance–cost. Table 3 demonstrates that there is enough diversity in the performance data of real services, which can ensure the effectiveness of our outcome. In addition, we assume that service #1 attempts to improve its performance–cost ratio by offering price discounts. Table 6 displays the preprocessed evaluation data for service #1 with different discounts expressed by CINS.

7.2. Experiment in risk-sensitive service selection mode

Example 1. Assume that a large-scale security company is ready to purchase a cloud service to store massive amounts of stock trading data; the 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 to 11:30 and from 13:00 to 15:00 every working day, the trustworthiness evaluation of the cloud service is more important during these two time periods than in other time periods. Based on this analysis of the user's requirements, we can define tradeoff coefficients for the time periods, as shown in Table 7.

According to the approach proposed in Section 6, the entropy value of the set $V = \{v_{ij}\}$ can be obtained using data from Table 5, yielding the results shown in Table 8.

Table 9 presents the entropies and weights of the time periods.

Table 10 shows the aggregation values of candidate services in the six target time periods.

Table 7
Tradeoff coefficients for time periods in Example 1.

F	F_1	F_2	F_3	F_4	F_5	F_6
α	0	0.6	0.6	0.6	0.6	0
β	0	0.8	1	1	0.8	0
γ	0	0.8	1	1	0.8	0

Table 8
Entropy values for set V in Example 1.

$E(V)$	T_1	T_2	T_3	T_4	T_5	T_6
$E(V_1)$	0.5918	0.8295	0.7747	0.7690	0.7606	0.5918
$E(V_2)$	0.5918	0.9230	0.9213	0.8518	0.8099	0.5918
$E(V_3)$	0.5918	0.8991	0.9180	0.9051	0.8974	0.5918
$E(V_4)$	0.5918	0.6960	0.7967	0.7803	0.7606	0.5918
$E(V_5)$	0.5918	0.8276	0.7629	0.7594	0.7575	0.5918
$E(V_6)$	0.5918	0.8306	0.7874	0.7925	0.7618	0.5918
$E(V_7)$	0.5918	0.9100	0.9042	0.8205	0.7997	0.5918
$E(V_8)$	0.5918	0.9133	0.8997	0.8801	0.8670	0.5918

Table 9
Entropies and the weights of time periods in Example 1.

Time periods	T_1	T_2	T_3	T_4	T_5	T_6
$E(T_i)$	1.0000	0.8503	0.8800	0.9247	0.9427	1.0000
$W(T_i)$	0.0000	0.3721	0.2983	0.1873	0.1423	0.0000

Table 10
Aggregation values of candidate services in Example 1.

Y	Aggregation values
y_1	{[0.2678, 1.0000], [0.1460, 0.8916], [0.0000, 0.1283]}
y_2	{[0.4733, 1.0000], [0.0138, 0.4884], [0.0000, 0.0085]}
y_3	{[0.5017, 1.0000], [0.0187, 0.4634], [0.0000, 0.0109]}
y_4	{[0.0825, 1.0000], [0.2304, 0.8916], [0.0000, 0.2479]}
y_5	{[0.2312, 1.0000], [0.1486, 0.8916], [0.0000, 0.1265]}
y_6	{[0.3091, 1.0000], [0.1281, 0.8916], [0.0000, 0.0979]}
y_7	{[0.4562, 1.0000], [0.0401, 0.5767], [0.0000, 0.0229]}
y_8	{[0.4962, 1.0000], [0.0314, 0.5154], [0.0000, 0.0179]}

The sort values of candidate services can be calculated using Eqs. (24)–(26), with the results shown in Table 11.

By comparing the sort values, the ranked list of services is finally obtained: $S_3 > S_2 > S_8 > S_7 > S_6 > S_1 > S_5 > S_4$. In other words, service #3 is the optimal candidate and will be recommended to the large-scale security company. The difference degree between our approach and the baseline is calculated according to Eqs. (28) and (27) shown in Table 12.

The result demonstrates that the difference degree is much less than 1.0. What is more important, the top four services in our services list are identical to the baseline list. In addition, the difference degree can be further decreased if there is enough training data used in searching the nearest neighbors of current user.

7.3. Experiment in performance-cost-sensitive service selection mode

Example 2. Assume that a small- and medium-sized logistics company is preparing to purchase a cloud service host to deploy their express delivery query application. The budget is very limited, and no highly confidential data is involved; 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 visiting time for this application is from 9:00 to 17:00 every working day. Based on this analysis of the user's requirements, we can define tradeoff coefficients for time periods as shown in Table 13.

The entropy value V can be obtained according to Table 5 and is shown in Table 14.

Table 11
Sort values of candidate services in Example 1.

Candidate services	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇	S ₈
$d^-(y_i, A^-)$	0.1515	0.0097	0.0004	0.2164	0.1578	0.1366	0.0324	0.0133
$d^+(y_i, A^+)$	0.0450	0.1884	0.1961	0.0199	0.0387	0.0599	0.1641	0.1832
Sort value	0.2288	0.9509	0.9980	0.0843	0.1971	0.3048	0.8351	0.9324
Ranking order	6	2	1	8	7	5	4	3

Table 12
Comparative analysis based on baseline in Example 1.

Candidate services	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇	S ₈
Baseline sort value	0.2159	0.9577	1.0000	0.0000	0.1180	0.0507	0.4391	0.5005
Baseline ranking order	5	2	1	8	6	7	4	3
d_i	0.2000	0.0000	0.0000	0.0000	0.1667	0.2857	0.0000	0.0000
D	0.6524							

Table 13
Tradeoff coefficients for time periods in Example 2.

F	F ₁	F ₂	F ₃	F ₄	F ₅	F ₆
α	0.8	0.8	1	1	1	0.8
β	0.6	0.6	0.6	0.6	0.6	0.6
γ	0.6	0.6	0.6	0.6	0.6	0.6

Table 14
Entropy values of set V in Example 2.

E(V)	T ₁	T ₂	T ₃	T ₄	T ₅	T ₆
E(V ₁)	0.8303	0.8295	0.7747	0.769	0.7606	0.7608
E(V ₂)	0.9501	0.923	0.9213	0.8518	0.8099	0.9168
E(V ₃)	0.8601	0.8991	0.918	0.9051	0.8974	0.8153
E(V ₄)	0.6883	0.696	0.7967	0.7803	0.7606	0.7722
E(V ₅)	0.8299	0.8276	0.7629	0.7594	0.7575	0.8554
E(V ₆)	0.8298	0.8306	0.7874	0.7925	0.7618	0.759
E(V ₇)	0.8324	0.91	0.9042	0.8205	0.7997	0.8162
E(V ₈)	0.8318	0.9133	0.8997	0.8801	0.867	0.867

Table 15
Entropies and weights of time periods in Example 2.

Time periods	T ₁	T ₂	T ₃	T ₄	T ₅	T ₆
E(T _i)	0.8576	0.8503	0.8800	0.9247	0.9427	0.9532
W(T _i)	0.2407	0.2531	0.2029	0.1274	0.0968	0.0792

Table 16
Aggregation values of candidate services in Example 2.

Y	Aggregation values
y ₁	{[0.4821, 1.0000], [0.0957, 0.6000], [0.0000, 0.0819]}
y ₂	{[0.7264, 1.0000], [0.0000, 0.2797], [0.0000, 0.0000]}
y ₃	{[0.7436, 1.0000], [0.0190, 0.3681], [0.0000, 0.0112]}
y ₄	{[0.1063, 1.0000], [0.1948, 0.6000], [0.0000, 0.2219]}
y ₅	{[0.4655, 1.0000], [0.0833, 0.5865], [0.0000, 0.0694]}
y ₆	{[0.5109, 1.0000], [0.0872, 0.6000], [0.0000, 0.0692]}
y ₇	{[0.6912, 1.0000], [0.0331, 0.4461], [0.0000, 0.0181]}
y ₈	{[0.7368, 1.0000], [0.0278, 0.4036], [0.0000, 0.0159]}

Table 15 presents the entropies and weights of the time periods. Table 16 shows the aggregation values of the candidate services in the six time periods.

Table 17 shows the sort values of the candidate services.

The ranked list of services is obtained by comparing the sort values: S₂ > S₃ > S₈ > S₇ > S₆ > S₁ > S₅ > S₄. In other words, service #2 is the optimal candidate and will be recommended to the logistics company. The difference degree between our approach and the baseline is shown in Table 18. According to Table 18, the sort order of six services in our ranked list is identical to the baseline list, including the top four services.

7.4. Experiment in low price competition mode

Example 3. Assume that service #1 adopts a low price strategy to improve its performance–cost ratio. When service #1 offers different discounts from 10% to 50%, its performance–cost ratio will change as shown in Table 6. In this case, we can again utilize our approach to help the security company in Example 1 and the logistics company in Example 2 to make their decisions. Table 19 displays the sort values of the candidate services in low price competition mode for comparative analysis between our approach and the baseline.

Table 19 shows that service #1 fails to increase its probability to be an optimal service or to obtain a distinct advantage, although it achieves an attractive performance–cost ratio. The service selection approach based on CINS consistently maintains the absolute dominance of service #3 for security company and the advantage of service #2 for logistics company.

7.5. Analysis and discussion

These experiments illustrate the following merits of the proposed approach:

- (1) Support for user preferences regarding time periods improves consumer satisfaction. Table 5 indicates that the evaluation data of service #3 in Example 1 is far from outstanding in time periods T₁ and T₆ in comparison with the other services, but service #3 becomes the optimal candidate by relying on its advantages in time periods T₃ and T₄. The security company does not care at all about time periods T₁ and T₆, while time periods T₃ and T₄ cover the period of stock exchange. Moreover, the tradeoff coefficients are set as $\alpha < \beta$ and $\alpha < \gamma$ in time periods T₂ ~ T₅ because the security company is more sensitive to potential risks than to performance–costs. An accurate analysis of time periods can help the security company find the most trustworthy candidate service.
- (2) Different service selection modes can produce ideal recommendation results. In Example 1’s risk-sensitive service selection mode, the assessment of potential risks plays a more important role than performance–cost ratio in evaluating candidate services, which leads to service #3 being judged as the most trustworthy candidate service. However, Example 2’s performance-cost-sensitive service selection mode shows an entirely different recommendation result, in which the service #2 is the most trustworthy candidate.
- (3) Prevent low-quality services with high performance–cost ratios from achieving an absolute advantage in competition with other services. In practice, some service providers adopt this low-price strategy to improve their performance–cost

Table 17
Sort values of candidate services in Example 2.

Candidate services	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
$d^-(y_i, A^-)$	0.1266	0.0029	0.0198	0.2290	0.1229	0.1182	0.0450	0.0291
$d^+(y_i, A^-)$	0.0791	0.2029	0.1860	0.0233	0.0828	0.0875	0.1607	0.1767
Sort value	0.3847	0.9861	0.9039	0.0924	0.4024	0.4252	0.7812	0.8588
Ranking order	7	1	2	8	6	5	4	3

Table 18
Comparative analysis based on baseline in Example 2.

Candidate services	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
Baseline sort value	0.4931	1.0000	0.9265	0.0000	0.2861	0.2646	0.7250	0.7549
Baseline ranking order	5	1	2	8	6	7	4	3
d_i	0.4000	0.0000	0.0000	0.0000	0.0000	0.2857	0.0000	0.0000
D	0.6857							

Table 19
Comparative analysis in low price competition mode.

Discounts	Application scenarios	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		
Security company	10%	0.2610	0.9509	0.9980	0.0843	0.1972	0.3048	0.8351	0.9324	6	5
	20%	0.2716	0.9510	0.9980	0.0844	0.1975	0.3051	0.8352	0.9325	6	5
	30%	0.2756	0.9510	0.9980	0.0846	0.1979	0.3055	0.8353	0.9326	6	5
	40%	0.2809	0.9510	0.9980	0.0848	0.1984	0.3059	0.8355	0.9327	6	5
	50%	0.2883	0.9511	0.9980	0.0850	0.1990	0.3065	0.8357	0.9329	6	5
Logistics company	10%	0.4461	0.9861	0.9039	0.0925	0.4025	0.4253	0.7812	0.8587	5	5
	20%	0.4564	0.9861	0.9038	0.0925	0.4028	0.4255	0.7812	0.8587	5	5
	30%	0.4594	0.9861	0.9037	0.0926	0.4032	0.4258	0.7812	0.8587	5	5
	40%	0.4634	0.9862	0.9036	0.0928	0.4037	0.4261	0.7812	0.8586	5	5
	50%	0.4690	0.9862	0.9034	0.0930	0.4043	0.4266	0.7812	0.8586	5	5

ratio for low-quality services. In our approach, the low-price strategy can increase 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 Table 19. The poor experience quality of a cloud service in indicators such as efficiency, availability or information security necessarily gives it high marks in the assessment of potential risks, which greatly reduces its probability of being a most trustworthy candidate. For example, according to Table 19, cloud service #1 has a fairly high performance–cost ratio; however, its assessment of potential risks shows very poor results. As a result, service #1 does not earn ideal sort values in Example 3.

- (4) The entropy weight measure method for CINS proposed in this paper can effectively manifest the differences between candidate services. The larger the entropy of a time period is, the smaller its weight should be. Although time period T_4 is very important to the security company in Example 1, the weights assigned to it by our method are much lower than the weight of time period T_2 , as shown in Table 9. The evaluation data of the candidate services in time period T_4 are very similar, such that assigning more weight to it does not help to identify the differences between candidates and find the most trustworthy service.

8. Conclusion

In the uncertain cloud computing environment, fluctuating QoS, flexible service pricing and complicated potential risks have always presented challenges to trustworthy service selection. Massive amounts of evaluation data regarding QoS, service cost and potential risks have created a critical issue in facilitating users to select trustworthy cloud services with tradeoffs between performance–costs and potential risks from abundant candidates.

Experiments based on real-world datasets demonstrate that the time period feature of cloud services can provide a new perspective to help solve this problem by accurately assessing the performance, cost and potential risks for cloud services.

This paper proposes a time series analysis approach to select trustworthy cloud service combined with INS theory, in which the original evaluation data about the performance–costs and potential risks of cloud services are preprocessed via cloud model method and measured with INS. In order to calculate and compare candidate services while supporting tradeoffs between performance–costs and potential risks during different time periods, we propose the CINS theory. We design its calculation rules and operators, and provide theoretical proofs in support. To address the problem of selecting trustworthy services with tradeoffs between performance–costs and potential risks in multiple time periods, we formulate the question as a MCDM problem of creating a ranked services list, and we develop a CINS ranking method to solve the problem. Experiments consisting of three numerical examples based on an appropriate baseline for comparative analysis demonstrate that the proposed approach can work effectively in both the risk-sensitive service selection mode and the performance-cost-sensitive service selection mode, and it can also prevent malignant price competition launched by low-quality services. This paper can provide a strong decision support approach for time-aware trustworthy service selection problem in cloud environment.

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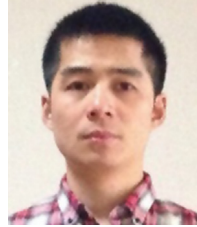
Appendix A. Supplementary data

Supplementary material related to this article can be found online at <http://dx.doi.org/10.1016/j.jpdc.2016.05.008>.

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