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Research Article

Using an Integrated Group Decision Method Based on SVM, TFN-RS-AHP, and TOPSIS-CD for Cloud Service Supplier Selection

Lian-hui Li,[1] Jiu-cheng Hang,[2] Yang Gao,[1] and Chun-yang Mu[1]

[1] *College of Mechatronic Engineering, Beifang University of Nationalities, Yinchuan 750021, China*
[2] *College of Electric and Information Engineering, Zhengzhou University of Light Industry, Zhengzhou 450002, China*

Correspondence should be addressed to Lian-hui Li; li_lianhui@163.com

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To solve the cloud service supplier selection problem under the background of cloud computing emergence, an integrated group decision method is proposed. The cloud service supplier selection index framework is built from two perspectives of technology and technology management. Support vector machine- (SVM-) based classification model is applied for the preliminary screening to reduce the number of candidate suppliers. A triangular fuzzy number-rough sets-analytic hierarchy process (TFN-RS-AHP) method is designed to calculate supplier's index value by expert's wisdom and experience. The index weight is determined by criteria importance through intercriteria correlation (CRITIC). The suppliers are evaluated by the improved TOPSIS replacing Euclidean distance with connection distance (TOPSIS-CD). An electric power enterprise's case is given to illustrate the correctness and feasibility of the proposed method.

1. Introduction

Cloud computing [1–4] is a new network application technology, and it is also a great revolution technology after the development of distributed computing, parallel computing, and grid computing. It is a kind of service mode based on shared infrastructure by which software, hardware, platform, and other IT resources will be available to users through the network services.

National Institute of Standards and Technology (NIST) has given its definition as follows: cloud computing is a kind of pay-per-use network operation mode which can provide users with available, convenient, on-demand use of network resources [5]. The resources including storage, application software, and computing services go into a configurable resource pool and can be quickly extracted and used. Enterprises do not have to invest a lot of management work; they only need to conduct the necessary interaction with the service providers. Currently, cloud computing is rapidly growing and can be applied in a mature way in many industries. For instance, Amazon, Google, Microsoft, and other IT giants have converted more and more applications into cloud services [1–7]. Cloud services [8] (i.e., cloud computing services) are cloud computing products which are available as a service and provided to users. Users can access the required resources and services in an on-demand and extensible way by the network. By updating to cloud service model, enterprises can effectively reduce the cost of investment, achieve the unified management of resources, sharing, and on-demand use and improve resource utilization. As a result, the market reaction capability and core competitiveness can be enhanced.

To develop and implement the cloud service-oriented networked mode for an enterprise or an enterprise union, the most important challenge is how to select the best cloud service supplier under the background of cloud computing emergence [9, 10]. The cloud services measurement initiative consortium (CSMIC) [11] has designed and released the service measurement index framework. Cloud service can

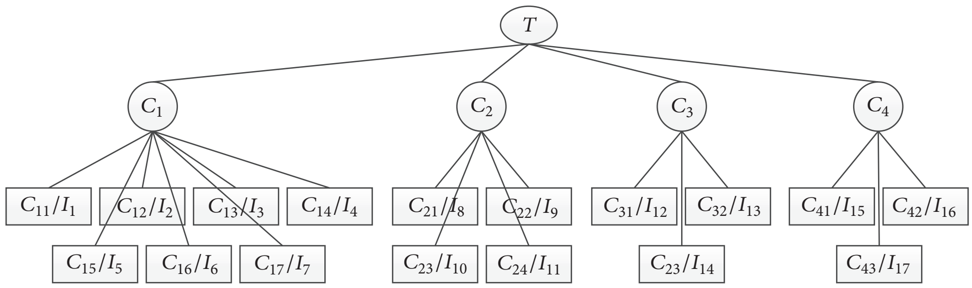

Figure 1: The cloud service supplier selection index framework.

be evaluated from seven aspects including accountability, agility, assurance, finance, performance, security privacy, and usability. Building the service medium between cloud service and application need based on this framework has gradually become an important development trend of cloud computing [12, 13].

Meanwhile, group decision method based on this framework has become a main method for cloud service supplier selection. Garg et al. proposed a framework for ranking of cloud computing services by analytic hierarchy process (AHP) [14]. Dong and Guo proposed an evaluation and selection approach for cloud manufacturing service based on template and global trust degree [15]. Generally, group decision method in existing researches can be divided into two categories: single methods and combination methods. Single methods mainly include AHP [16], ANP [17], rough sets [18], DEA [19], grey theory [20], fuzzy axiomatic design [21], fuzzy TOPSIS [22], genetic algorithm [23], and COWA operator [24]. Combination methods mainly include threshold method and grey relational analysis [25], AHP and genetic algorithm [26], ANN-MADA [27], ANP-DEA [28], fuzzy DEMATEL-ANP-TOPSIS [29], fuzzy AHP and fuzzy multiobjective linear programming [30], AHP-ISM [31], and AHP-TOPSIS [32].

Through the analysis of the existing researches, it can be summarized that cloud service is considered more on the technology perspective but less on the technology management perspective based on the service measurement index framework. Meanwhile, the uncertain preference information processing is lacked. Therefore, we put forward an integrated group decision method for cloud service supplier selection. From two perspectives of technology and technology management, we build the cloud service supplier selection index framework by four criteria: cloud service performance, supplier capability, supplier service level, and supplier service quality. According to the main information of candidate suppliers, support vector machine- (SVM-) based classification model is applied for the preliminary screening to reduce the number of candidate suppliers. Through the investigation and mastery of experts to all suppliers on the indexes, a triangular fuzzy number-rough sets-AHP (TFN-RS-AHP) method is proposed to calculate supplier's index value by expert's wisdom and experience. The index weight is determined by criteria importance though intercriteria correlation (CRITIC). Finally, the suppliers are evaluated by improved TOPSIS replacing Euclidean distance with connection distance.

2. Index Framework

Cloud service supplier selection index framework is one of the most important problems in the whole evaluation process. CSMIC has given the service measurement index framework. In this framework, cloud service can be evaluated from seven aspects including accountability, agility, assurance, finance, performance, security privacy, and usability. It can be seen that this framework is mainly from the technology perspective.

Different suppliers can provide similar or the same cloud service, so cloud service supplier selection is different from cloud service selection. Additionally, cloud service supplier selection has some inherent relevance to the application industry.

Considering the characteristics of cloud service supplier from the technology perspective and the technology management perspective, the cloud service supplier selection index framework is built as shown in Figure 1 by four criteria (C_1: cloud service performance, C_2: supplier capability, C_3: supplier service level, and C_4: supplier service quality) according to systematic, comprehensive, scientific, flexible, and operable principles.

Cloud service performance criterion, which includes the core content of CSMIC's service measurement index framework, embodies the technology perspective. Supplier capability criterion, supplier service level criterion, and supplier service quality criterion embody the technology management perspective. Each criterion is further detailed to indexes. The significance of each index is as follows: C_{11}/I_1: service resource's virtualization management, C_{12}/I_2: service's coordination, integration, and intelligence, C_{13}/I_3: service mode's diversity, C_{14}/I_4: service's maintainability, availability, and flexibility, C_{15}/I_5: service data's transmission and storage security, access security, and privacy protection, C_{16}/I_6: service's timeliness, accuracy, reliability, fault tolerance, and

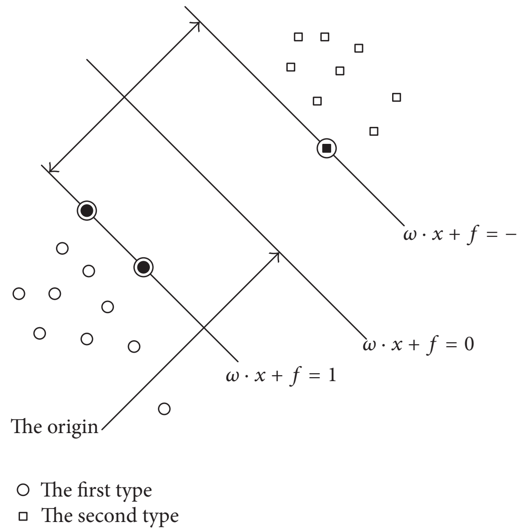

Figure 2: The optimal separating hyperplane of SVM.

robustness, C_{17}/I_7: service's deployment cost, running cost, and maintenance cost, C_{21}/I_8: supplier's operation management and organization management level, C_{22}/I_9: supplier's technical support and training level, C_{23}/I_{10}: supplier's reputation and implementation experience, C_{24}/I_{11}: supplier's ability of research development, innovation, and profitability, C_{31}/I_{12}: supplier's service attitude and sustainability, C_{32}/I_{13}: supplier's ability to provide value-added and extended services, C_{33}/I_{14}: supplier's ability of service deployment, running, and maintenance, C_{41}/I_{15}: supplier service's timely delivery and stability, C_{42}/I_{16}: supplier service's protocol level and execution ability, and C_{43}/I_{17}: supplier service's cost-effectiveness.

3. Integrated Group Decision Method

3.1. Preliminary Screening. Under the linear separable circumstances, the basic idea of SVM [33, 34] can be described as follows. It is assumed that the samples are $(x_1, y_1), \ldots, (x_l, y_l)$, $x \in R^u$, where l is the number of samples and u is the number of input dimensions. A hyperplane is defined as $\omega \cdot x + f = 0$ to classify the samples into two types. The classification result is as follows:

$$\begin{aligned} \omega \cdot x_i + f &\geq 0, \\ y_i &= +1 \\ \omega \cdot x_i + f &\geq 0, \\ y_i &= -1, \end{aligned} \tag{1}$$

where ω is the adjustable weight vector and f is the bias amount of the hyperplane. So $\omega \cdot x$ represents the scalar product of $\omega \in R^u$ and $x_i \in R^u$.

The optimal classification hyperplane is shown in Figure 2.

To achieve the correct classification of all samples, the classification intervals $2/\|w\|$ on both sides should be the largest. Finding the optimal hyperplane can be considered as the quadratic programming problem. For the training sample set, the optimal value of w and b should be found to minimize the cost function; that is,

$$\min \quad \varphi(w) = \frac{\|w\|^2}{2} = \frac{\omega^{\mathrm{T}}\omega}{2}, \tag{2}$$

where the constraint condition is $y_i(\omega \cdot x_i + f) - 1 \geq 0$, $i = 1, 2, \ldots, l$.

Here the optimization function is quadratic form and the constraint condition is linear, so this is a typical quadratic programming problem which can be solved by Lagrange method. The Lagrange multiplier is $\xi_i \geq 0$, $i = 1, 2, \ldots, l$, so

$$\Gamma(\omega, f, \xi) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{l} \xi_i \left(y_i \left(\omega \cdot x_i + f \right) - 1 \right). \tag{3}$$

The extreme of Γ belongs to saddle point. The minimum of ω and f to Γ can be obtained as $\omega = \omega^*$ and $f = f^*$ while the maximum of ξ to Γ can be obtained as $\xi = \xi^*$. The optimal hyperplane can be determined by solving quadratic program problem based on the derivative of Γ. As can be seen, only the samples which make $\xi = 0$ can play a role in ω^* and determine the classification result. These samples are defined as support vectors. Then ω^* is obtained as follows:

$$\omega^* = \sum_{i=1}^{l} \xi_i^* y_i x_i. \tag{4}$$

One support vector sample $x_i : f^* = y_i - \omega \cdot x_i$ is selected. For any input sample x, the classification function is as follows:

$$d(x) = \omega^* \cdot x + f^* = \Gamma(\omega, f, \xi) = \sum_{i=1}^{l} y_i \xi_i^* (x x_i) + f. \tag{5}$$

The ascription of x is determined according to the positive or negative sign of $d(x)$. If the samples are linear nonseparable, the linear nonseparable problem can be converted to linear separable problem by nonlinear transformation defined by kernel function.

3.2. Index Value Calculating. By rough sets theory [35], the domain U is a nonnull finite set of the objects and Y is an object in U. All objects in U belong to p partitions: $S_1, S_2, \ldots, S_p$. These p partitions have an order: $S_1 < S_2 < \cdots < S_p$. To any partition S_i $(1 \leq i \leq p)$, its upper approximation set is $\mathrm{AS}^{\mathrm{Upper}}(S_i) = \{Y \in K \mid K \subseteq U/R(Y) \wedge K \geq S_i\}$ and its lower approximation set is $\mathrm{AS}^{\mathrm{Lower}}(S_i) = \{Y \in K \mid K \subseteq U/R(Y) \wedge K \leq S_i\}$, where $U/R(Y)$ indicates the partition of the unclear relationship R in the domain U. Any unclear partition S_i in the domain U can be expressed by its rough number. The rough number of S_i is composed of the upper bound $L^{\mathrm{Upper}}(S_i) = (\sum R(Y))/N^{\mathrm{Upper}}(S_i)$, $Y \in \mathrm{AS}^{\mathrm{Upper}}(S_i)$, and the lower bound $L^{\mathrm{Lower}}(S_i) = (\sum R(Y))/N^{\mathrm{Lower}}(S_i)$, $Y \in \mathrm{AS}^{\mathrm{Lower}}(S_i)$; here $N^{\mathrm{Upper}}(S_i)$ is the number of objects contained in the upper approximation set of S_i and $N^{\mathrm{Lower}}(S_i)$ is the number of objects contained in the lower approximation set of S_i. The interval between upper and lower bounds is defined as the rough boundary interval $RN(S_i) = [L^{\mathrm{Lower}}(S_i), L^{\mathrm{Upper}}(S_i)]$. Therefore, the unclear partition S_i in the domain U can be expressed by the rough boundary interval $RN(S_i) = [L^{\mathrm{Lower}}(S_i), L^{\mathrm{Upper}}(S_i)]$ which contains its upper bound and lower bound.

The mathematical statistics characteristic of expert scoring method can maximize the values of expert's wisdom and experience. However, the scores of multiple cloud service suppliers on an index depend on expert's personal experience and subjective judgment. Expressing the score with a certain number is obviously unreasonable. Compared with certain number, fuzzy number can better reflect the inherent uncertainty of expert scoring. Additionally, the uncertainty can be described as set boundary region by the rough boundary interval. Compared with membership function, set boundary region can better reflect the real judgment of expert and the views of multiple experts can be taken into account. Therefore, a triangular fuzzy number-rough sets-AHP (TFN-RS-AHP) method is proposed to calculate the index value of cloud service supplier.

It is assumed that there are n cloud service suppliers after preliminary screening and q experts. To the index I_t $(t = 1, 2, \ldots, 17)$, the TFN score matrices given by q experts are $E_{1,t}, E_{2,t}, \ldots, E_{q,t}$, where $E_{k,t} = (e_{i,j}^{k,t})_{n\times n}$ $(k = 1, 2, \ldots, q$ and $i, j = 1, 2, \ldots, n)$. When $i \neq j$, $e_{i,j}^{k,t} = (a_{i,j}^{k,t}, b_{i,j}^{k,t}, c_{i,j}^{k,t})$ represents the score of the cloud service supplier j relative to the cloud service supplier i on the index I_t given by the expert k. When $i = j$, $e_{i,j}^{k,t} = (1, 1, 1)$. These matrices $E_{1,t}, E_{2,t}, \ldots, E_{q,t}$ must pass the consistency inspection. If $E_{k,t}$ fails, it will be modified by the expert k.

Step 1. $E_{k,t}$ is decomposed into $A_{k,t} = (a_{i,j}^{k,t})_{n\times n}$, $B_{k,t} = (b_{i,j}^{k,t})_{n\times n}$, and $C_{k,t} = (c_{i,j}^{k,t})_{n\times n}$. $A_{1,t}, A_{2,t}, \ldots, A_{q,t}$ are combined together into a rough group decision matrix $A_t = (A_{i,j}^{t})_{n\times n}$, where $A_{i,j}^{t} = \{a_{i,j}^{1,t}, a_{i,j}^{2,t}, \ldots, a_{i,j}^{q,t}\}$.

Step 2. The rough boundary intervals of the scores given by q experts in $A_{i,j}^{t}$ are $RN(a_{i,j}^{1,t}), RN(a_{i,j}^{2,t}), \ldots, RN(a_{i,j}^{q,t})$, where $RN(a_{i,j}^{k,t}) = [a_{i,j}^{k-,t}, a_{i,j}^{k+,t}]$, $k = 1, 2, \ldots, q$. Then $RN(A_{i,j}^{t}) = \{[a_{i,j}^{1-,t}, a_{i,j}^{1+,t}], [a_{i,j}^{2-,t}, a_{i,j}^{2+,t}], \ldots, [a_{i,j}^{q-,t}, a_{i,j}^{q+,t}]\}$. As a result, the average rough interval of $A_{i,j}^{t}$ is as follows:

$$RN\left(A_{i,j}^{t}\right) = \left[a_{i,j}^{-,t}, a_{i,j}^{+,t}\right] = \left[\frac{\sum_{r=1}^{q} a_{i,j}^{r-,t}}{q}, \frac{\sum_{r=1}^{q} a_{i,j}^{r+,t}}{q}\right]. \quad (6)$$

Step 3. The rough judgment matrix can be obtained as $EA_t = (RN(A_{i,j}^{t}))_{n\times n}$. EA_t can be decomposed into the rough lower boundary matrix EA_t^{-} and the rough upper boundary matrix EA_t^{+}, where $EA_t^{-} = (a_{i,j}^{-,t})_{n\times n}$ and $EA_t^{+} = (a_{i,j}^{+,t})_{n\times n}$. Their characteristic vectors corresponding to the maximum eigenvalue are, respectively, obtained as $VA_t^{-} = [va_1^{-,t}, va_2^{-,t}, \ldots, va_n^{-,t}]^{\mathrm{T}}$ and $VA_t^{+} = [va_1^{+,t}, va_2^{+,t}, \ldots, va_n^{+,t}]^{\mathrm{T}}$. After averaging, $ga_i^{t} = (|va_i^{-,t}| + |v_i^{a+,t}|)/2$, $i = 1, 2, \ldots, n$. We can get $GA_t = \{ga_1^{t}, ga_2^{t}, \ldots, ga_n^{t}\}$.

Step 4. Similarly, $GB_t = \{gb_1^{t}, gb_2^{t}, \ldots, gb_n^{t}\}$ and $GC_t = \{gc_1^{t}, gc_2^{t}, \ldots, gc_n^{t}\}$ can be obtained. Consequently, the values of n cloud service suppliers on the index I_t are $z_{1,t}, z_{2,t}, \ldots, z_{n,t}$, where $z_{i,t} = (ga_i^{t}, gb_i^{t}, gc_i^{t})$ is a triangular fuzzy number.

Step 5. Using the same method, the value of n cloud service suppliers on other indexes can be obtained. The triangular fuzzy number index value matrix can be expressed as $Z = (z_{i,t})_{n\times m}$.

Step 6. The methods of converting triangular fuzzy number into real number mainly are gravity center method and mean square deviation method. To the triangular fuzzy number index value $z_{i,t} = (ga_i^{t}, gb_i^{t}, gc_i^{t})$, its gravity center [36, 37] is $c(z_{i,t}) = (ga_i^{t} + gb_i^{t} + gc_i^{t})/3$, and its mean square deviation [36, 37] is

$$\sigma(z_{i,t}) = \sqrt{\left|\frac{(ga_i^{t})^2 + (gb_i^{t})^2 + (gc_i^{t})^2 - ga_i^{t}\cdot gb_i^{t} - ga_i^{t}\cdot gc_i^{t} - gb_i^{t}\cdot gc_i^{t}}{18}\right|}. \quad (7)$$

Here, we construct a planning model by introducing the risk preference factor to realize the integration of the two methods. It is assumed that the decision makers tend to use the gravity center method with a risk preference of ξ_i and tend to use the mean square deviation method with a risk preference of $1 - \xi_i$. ξ_i and $1 - \xi_i$ are used as the weight of gravity center and mean square deviation, respectively. The triangular fuzzy number $z_{i,t}$ can be described as $d_{i,t} = (\xi_i \cdot c(z_{i,t}))^2 + ((1 - \xi_i)\cdot \sigma(z_{i,t}))^2$.

We construct the planning model: min $d_{i,t}$, s.t. $0 \le \xi_i \le 1$. The risk preference ξ_i can be obtained as follows:

$$\xi_i = \frac{(c(z_{i,t}))^2}{(c(z_{i,t}))^2 + (\sigma(z_{i,t}))^2}. \tag{8}$$

As a result, the triangular fuzzy number index value matrix of n cloud service suppliers can be converted into the real number form $D = (d_{i,t})_{n\times m}$.

The index value matrix $D = (d_{i,t})_{n\times m}$ should be standardized as follows:

$$d_{i,t} = \frac{d_{i,t} - \overline{d_{,t}}}{\sqrt{\operatorname{var}(d_{,t})}}, \tag{9}$$

where $\overline{d_{,t}} = (1/n)\sum_{i=1}^{n} d_{i,t}$ and $\operatorname{var}(d_{,t}) = (1/(n-1))\sum_{i=1}^{n}(d_{i,t} - \overline{d_{,t}})^2$.

3.3. Index Weight Determining. Assuming that the vector of index weight is $\Phi = [\phi_1, \phi_2, \ldots, \phi_m]^{\mathrm{T}}$, weighting methods commonly include entropy method [38], standard deviation method [39], and CRITIC [40].

3.3.1. Entropy Method [38]. According to the entropy theory, the entropy value of the index I_t $(t = 1, 2, \ldots, 17)$ is as follows:

$$EV_t = -\frac{1}{\ln m}\sum_{i=1}^{n}\frac{d_{i,t}}{d_{,t}}\ln\frac{d_{i,t}}{d_{,t}}, \tag{10}$$

where $d_{,t} = \sum_{i=1}^{n} d_{i,t}$.

The larger entropy value means that the values of all cloud service suppliers on I_t have a smaller difference. It is generally believed that the index is more important when the values of all suppliers have a larger difference. So the weight of I_t is as follows:

$$\phi_t = \frac{(1 - EV_t)}{\sum_{t=1}^{m}(1 - EV_t)}. \tag{11}$$

3.3.2. Standard Deviation Method [39]. The standard deviation of the index I_t is σ_t, so the weight of I_t is as follows:

$$\phi_t = \frac{\sigma_t}{\sum_{t=1}^{m}\sigma_t}, \tag{12}$$

where $\sigma_t = \sqrt{(1/n)\sum_{i=1}^{n}(d_{i,t} - (1/n)\sum_{i=1}^{n} d_{i,t})^2}$.

3.3.3. CRITIC [40]. The comparison strength with the expression form of standard deviation indicates the value difference of all objects on the same index. The conflict is based on the correlation between two indexes. When the two indexes have a strong positive correlation, the conflict is low. Both comparison strength and conflict should be considered comprehensively.

The correlation coefficient [40] of the indexes I_k and I_j is as follows:

$$\mathrm{ccr}_{k,j} = \frac{\sum_{i=1}^{n}(d_{i,k} - (1/n)\sum_{i=1}^{n} d_{i,k})(d_{i,j} - (1/n)\sum_{i=1}^{n} d_{i,j})}{\sqrt{\sum_{i=1}^{n}(d_{i,k} - (1/n)\sum_{i=1}^{n} d_{i,k})^2}\sqrt{\sum_{i=1}^{n}(d_{i,j} - (1/n)\sum_{i=1}^{n} d_{i,j})^2}}. \tag{13}$$

The conflict of the index I_j with other indexes can be expressed as follows:

$$\mathrm{con}_j = \sum_{k=1}^{m}(1 - \mathrm{ccr}_{k,j}). \tag{14}$$

Therefore, the weight of I_j is as follows:

$$\phi_j = \frac{C_j}{\sum_{j=1}^{m} C_j}, \tag{15}$$

where $C_j = \sigma_j \cdot \mathrm{con}_j$ is the information amount of I_j.

Compared with entropy method and standard deviation method, CRITIC, which comprehensively considers the volatility of index value and the conflict between the indexes, can completely reflect the competitive relationship between the indexes. As a result, we choose CRITIC to determine the index weight.

3.4. Suppliers Evaluating. The technique for order preference by similarity to an ideal solution (TOPSIS) is a classic multi-index sorting method [41]. Euclidean distances between the object and two ideal points are used to calculate the closeness. The objects on the perpendicular bisector of two ideal points have the same closeness value and cannot be distinguished. Therefore, some improved TOPSIS methods have been proposed such as angle measure evaluation method (TOPSIS-AME) [42] and vertical projection method (TOPSIS-VP) [43]. The former one only considers the angle closeness between the object and two ideal points and ignores the difference in length. When two objects have the same angle closeness but different length, it will draw the wrong conclusion. When two or more objects have the same projective point on the connection line of two ideal points, the latter one also cannot distinguish these objects.

The theory of set pair analysis (SPA) [44, 45], proposed by Zhao in 1989, is a systematic analysis method to solve the uncertainty problem with connection degree. A set pair is constructed from two related sets in the uncertainty system; then the sameness, contrariety, and difference analysis will be done on the uncertainty of the set pair; lastly the connection degree of the set pair can be obtained. SPA method can be used to describe the relationship in certainty-uncertainty system.

According to the index value matrix $D = (d_{i,t})_{n\times m}$ and the index weight vector $\Phi = [\phi_1, \phi_2, \ldots, \phi_m]^{\mathrm{T}}$, we can get the weighted index value matrix $H = (h_{i,j})_{n\times m} = (\phi_j \cdot d_{i,j})_{n\times m}$.

The positive ideal point and the negative ideal point are as follows:

$$H^{+} = [h_1^{+}, h_2^{+}, \ldots, h_l^{+}],$$
$$H^{-} = [h_1^{-}, h_2^{-}, \ldots, h_l^{-}], \tag{16}$$

where $h_i^{+} = \max\{h_{1,i}, h_{2,i}, \ldots, h_{n,i}\}$ and $h_i^{-} = \min\{h_{1,i}, h_{2,i}, \ldots, h_{n,i}\}$.

The weighted index value of the supplier k ($k = 1, 2, \ldots, n$) can be expressed as H^k which is the row k of H.

The element pairs $(h_{k1}, h_1^{+}), (h_{k2}, h_2^{+}), \ldots, (h_{kl}, h_l^{+})$ are comprised of the corresponding elements of H^k and H^{+}. Comparing the element pairs $(h_{k1}, h_1^{+}), (h_{k2}, h_2^{+}), \ldots, (h_{kl}, h_l^{+})$, there are $N_{k,+}^{1}$ pairs in which the difference of h_{ki} and h_i^{+} is tiny (i.e., sameness relationship), $N_{k,+}^{2}$ pairs in which the difference of h_{ki} and h_i^{+} is huge (i.e., contrariety relationship), and $N_{k,+}^{3}$ pairs in which the difference of h_{ki} and h_i^{+} is existing but not very obvious (i.e., difference relationship) [44, 45]. $N_{k,+}^{1} + N_{k,+}^{2} + N_{k,+}^{3} = l$. So the connection degree between H^k and H^{+} can be expressed as $D(H^k, H^{+}) = (N_{k,+}^{1}/l)\Delta + (N_{k,+}^{2}/l)\Omega + (N_{k,+}^{3}/l)\Psi$, where Δ, Ω, and Ψ are the symbols of the sameness relationship, contrariety relationship, and difference relationship.

We assume that $D(H^k, H^{+}) = \Theta_1 \cdot D(h_{k1}, h_1^{+}) + \Theta_2 \cdot D(h_{k2}, h_2^{+}) + \cdots + \Theta_l \cdot D(h_{kl}, h_l^{+})$, where $D(h_{ki}, h_1^{+}) = A_{ki}^{+} \cdot \Delta + B_{ki}^{+} \cdot \Omega + C_{ki}^{+} \cdot \Psi$, $i = 1, 2, \ldots, m$. If $h_{ki} = h_i^{-}$, $A_{ki}^{+} = C_{ki}^{+} = 0$ and $B_{ki}^{+} = 1$; and if $h_{k,i} \in (h_i^{-}, h_i^{+})$, $A_{ki}^{+} = h_{ki}/h_i^{+}$, $C_{ki}^{+} = 1 - h_{ki}/h_i^{+}$, and $B_{ki}^{+} = 0$; and if $h_{ki} = h_i^{+}$, $A_{ki}^{+} = 1$ and $B_{ki}^{+} = C_{ki}^{+} = 0$. So we can get the connection degree between H^k and H^{+} as follows:

$$D\left(H^k, H^{+}\right) = A_k^{+}\Delta + B_k^{+}\Omega + C_k^{+}\Psi, \tag{17}$$

where $A_k^{+} = (\sum_{i=1}^{l} A_{ki}^{+})/l$, $B_k^{+} = (\sum_{i=1}^{l} B_{ki}^{+})/l$, $C_k^{+} = (\sum_{i=1}^{l} C_{ki}^{+})/l$.

According to SPA theory, the connection vector between H^k and H^{+} can be expressed as $V(H^k, H^{+}) = (A_k^{+}, B_k^{+}, C_k^{+})^{\mathrm{T}}$ and the connection vector between H^{+} and itself is $V(H^{+}, H^{+}) = (1, 0, 0)^{\mathrm{T}}$, so the connection distance from H^k to H^{+} is $d(H^k, H^{+}) = \sqrt{(A_k^{+} - 1)^2 + (B_k^{+})^2 + (C_k^{+})^2}$.

Similarly, we can get that the connection distance from H^k to H^{-} is $d(H^k, H^{-}) = \sqrt{(A_k^{-} - 1)^2 + (B_k^{-})^2 + (C_k^{-})^2}$.

Lastly, we can get the relative closeness degree from H^k to the ideal points H^{+} and H^{-}as follows:

$$\mathrm{rc}_k = \frac{d\left(H^k, H^{-}\right)}{d\left(H^k, H^{+}\right) + d\left(H^k, H^{-}\right)}. \tag{18}$$

The relative closeness degree rc_k has the following characteristics:

(1) If $H^k = H^{+}$, $\mathrm{rc}_k = 1$.

(2) If $H^k = H^{-}$, $\mathrm{rc}_k = 0$.

(3) When $d(H^k, H^{+}) \to 0$ (i.e., $H^k \neq H^{+}$ and $H^k \neq H^{-}$, $H^k \to H^{+}$), $\mathrm{rc}_k \to 1$.

Therefore, using the connection distance from the object to the ideal points fits well with the basic sorting principles of TOPSIS, so the improved TOPSIS by replacing Euclidean distance with connection distance (TOPSIS-CD) is reasonable. We can calculate the relative closeness from each object to the ideal points successively and obtain the final results by sorting them.

4. Case Study

With the rapid development in electric power industry and the continuous improvement of the customers' requirement for electric safety, the traditional vertical mode is gradually hard to guarantee the whole process of electric power industry under the certain cost and periodic constraints. The service-oriented networked mode, which combines the IT capacity with the traditional electric power industry, provides an effective solution to this problem and realizes the rapid integrating and updating of electric power enterprises. Cloud service platform has greatly facilitated the deep collaboration among different enterprises in the electric power chain. More importantly, the electric power enterprises can gradually shift to service-oriented pattern through the cloud service platform, and the enterprise's independent innovation and core competitiveness can be continuously improved.

To meet the development requirement, the management team of an electric power enterprise has decided to introduce the service-oriented networked mode after careful analysis and discussion.

Several important indexes in Figure 1 chosen by decision makers are taken as the standard to determine the input vector. According to Formula (2), the classification function can be determined. Due to limited space, the detailed index information is not given. The process of preliminary screening for cloud service supplier selection using SVM classification model is as follows. If $d(x) = \omega^{*} \cdot x + f^{*} \geq 0$, x will pass. If $d(x) = \omega^{*} \cdot x + f^{*} < 0$, x will be eliminated. We use SVM toolbox in Matlab to classify twelve qualified suppliers and five suppliers (S_1, S_2, S_3, S_4, and S_5) pass the preliminary screening.

Taking the index I_1 as an example, the TFN score matrices of five suppliers given by three experts are $E_{1,1} = (e_{i,j}^{1,1})_{5\times5}$, $E_{2,1} = (e_{i,j}^{2,1})_{5\times5}$, and $E_{3,1} = (e_{i,j}^{3,1})_{5\times5}$, where $e_{i,j}^{1,1} = (a_{i,j}^{1,1}, b_{i,j}^{1,1}, c_{i,j}^{1,1})$, $e_{i,j}^{2,1} = (a_{i,j}^{2,1}, b_{i,j}^{2,1}, c_{i,j}^{2,1})$, and $e_{i,j}^{3,1} = (a_{i,j}^{3,1}, b_{i,j}^{3,1}, c_{i,j}^{3,1})$. Here,

$$E_{1,1}=\begin{bmatrix} (1,1,1) & \left(\frac{7}{8},1,\frac{13}{9}\right) & (4,5,6) & (7,8,8) & \left(\frac{5}{2},3,\frac{7}{2}\right) \\ \left(\frac{9}{13},1,\frac{8}{7}\right) & (1,1,1) & \left(2,\frac{5}{2},3\right) & \left(4,\frac{9}{2},\frac{11}{2}\right) & \left(\frac{1}{2},1,\frac{3}{2}\right) \\ \left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right) & \left(\frac{1}{3},\frac{2}{5},\frac{1}{2}\right) & (1,1,1) & \left(\frac{3}{4},1,\frac{6}{5}\right) & \left(\frac{6}{11},\frac{7}{8},1\right) \\ \left(\frac{1}{8},\frac{1}{8},\frac{1}{7}\right) & \left(\frac{2}{11},\frac{2}{9},\frac{1}{4}\right) & \left(\frac{5}{6},1,\frac{4}{3}\right) & (1,1,1) & \left(\frac{1}{4},\frac{1}{3},\frac{1}{3}\right) \\ \left(\frac{2}{7},\frac{1}{3},\frac{2}{5}\right) & \left(\frac{2}{3},1,2\right) & \left(1,\frac{8}{7},\frac{11}{6}\right) & (3,3,4) & (1,1,1) \end{bmatrix},$$

$$E_{2,1}=\begin{bmatrix} (1,1,1) & \left(\frac{5}{6},1,\frac{4}{3}\right) & \left(\frac{1}{3},\frac{2}{5},\frac{1}{2}\right) & \left(1,\frac{8}{7},\frac{11}{6}\right) & \left(4,\frac{9}{2},\frac{11}{2}\right) \\ \left(\frac{3}{4},1,\frac{6}{5}\right) & (1,1,1) & \left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right) & \left(\frac{2}{7},\frac{1}{3},\frac{2}{5}\right) & \left(\frac{1}{2},1,\frac{3}{2}\right) \\ \left(2,\frac{5}{2},3\right) & (4,5,6) & (1,1,1) & \left(\frac{7}{8},1,\frac{13}{9}\right) & (7,8,8) \\ \left(\frac{6}{11},\frac{7}{8},1\right) & \left(\frac{5}{2},3,\frac{7}{2}\right) & \left(\frac{9}{13},1,\frac{8}{7}\right) & (1,1,1) & \left(\frac{1}{4},\frac{1}{3},\frac{1}{3}\right) \\ \left(\frac{2}{11},\frac{2}{9},\frac{1}{4}\right) & \left(\frac{2}{3},1,2\right) & \left(\frac{1}{8},\frac{1}{8},\frac{1}{7}\right) & (3,3,4) & (1,1,1) \end{bmatrix}, \quad (19)$$

$$E_{3,1}=\begin{bmatrix} (1,1,1) & (3,3,4) & \left(\frac{1}{3},\frac{2}{5},\frac{1}{2}\right) & \left(\frac{2}{7},\frac{1}{3},\frac{2}{5}\right) & \left(\frac{1}{8},\frac{1}{8},\frac{1}{7}\right) \\ \left(\frac{1}{4},\frac{1}{3},\frac{1}{3}\right) & (1,1,1) & (4,5,6) & \left(\frac{5}{6},1,\frac{4}{3}\right) & \left(\frac{1}{2},1,\frac{3}{2}\right) \\ \left(2,\frac{5}{2},3\right) & \left(\frac{1}{6},\frac{1}{5},\frac{1}{4}\right) & (1,1,1) & \left(\frac{2}{11},\frac{2}{9},\frac{1}{4}\right) & \left(\frac{6}{11},\frac{7}{8},1\right) \\ \left(\frac{5}{2},3,\frac{7}{2}\right) & \left(\frac{3}{4},1,\frac{6}{5}\right) & \left(4,\frac{9}{2},\frac{11}{2}\right) & (1,1,1) & \left(\frac{7}{8},1,\frac{13}{9}\right) \\ (7,8,8) & \left(\frac{2}{3},1,2\right) & \left(1,\frac{8}{7},\frac{11}{6}\right) & \left(\frac{9}{13},1,\frac{8}{7}\right) & (1,1,1) \end{bmatrix}.$$

All of them can pass the consistency inspection.

We decompose $E_{1,1}$ into $A_{1,1}$, $B_{1,1}$, and $C_{1,1}$, decompose $E_{2,1}$ into $A_{2,1}$, $B_{2,1}$, and $C_{2,1}$, and decompose $E_{3,1}$ into $A_{3,1}$, $B_{3,1}$, and $C_{3,1}$, respectively.

$$A_{1,1}=\begin{bmatrix} 1 & \frac{7}{8} & 4 & 7 & \frac{5}{2} \\ \frac{9}{13} & 1 & 2 & 4 & \frac{1}{2} \\ \frac{1}{6} & \frac{1}{3} & 1 & \frac{3}{4} & \frac{6}{11} \\ \frac{1}{8} & \frac{2}{11} & \frac{5}{6} & 1 & \frac{1}{4} \\ \frac{2}{7} & \frac{2}{3} & 1 & 3 & 1 \end{bmatrix}, \quad A_{2,1}=\begin{bmatrix} 1 & \frac{5}{6} & \frac{1}{3} & 1 & 4 \\ \frac{3}{4} & 1 & \frac{1}{6} & \frac{2}{7} & \frac{1}{2} \\ 2 & 4 & 1 & \frac{7}{8} & 7 \\ \frac{6}{11} & \frac{5}{2} & \frac{9}{13} & 1 & \frac{1}{4} \\ \frac{2}{11} & \frac{2}{3} & \frac{1}{8} & 3 & 1 \end{bmatrix}, \quad A_{3,1}=\begin{bmatrix} 1 & 3 & \frac{1}{3} & \frac{2}{7} & \frac{1}{8} \\ \frac{1}{4} & 1 & 4 & \frac{5}{6} & \frac{1}{2} \\ 2 & \frac{1}{6} & 1 & \frac{2}{11} & \frac{6}{11} \\ \frac{5}{2} & \frac{3}{4} & 4 & 1 & \frac{7}{8} \\ 7 & \frac{2}{3} & 1 & \frac{9}{13} & 1 \end{bmatrix}. \quad (20)$$

$A_{1,1}$, $A_{2,1}$, and $A_{3,1}$ are combined together into a rough group decision matrix $A_1 = (A^1_{i,j})_{5\times5}$, $A^1_{i,j} = \{a^{1,1}_{i,j}, a^{2,1}_{i,j}, a^{3,1}_{i,j}\}$.

$$A_1 = \begin{bmatrix} \{1,1,1\} & \left\{\frac{7}{8},\frac{5}{6},3\right\} & \left\{4,\frac{1}{3},\frac{1}{3}\right\} & \left\{7,1,\frac{2}{7}\right\} & \left\{\frac{5}{2},4,\frac{1}{8}\right\} \\ \left\{\frac{9}{13},\frac{3}{4},\frac{1}{4}\right\} & \{1,1,1\} & \left\{2,\frac{1}{6},4\right\} & \left\{4,\frac{2}{7},\frac{5}{6}\right\} & \left\{\frac{1}{2},\frac{1}{2},\frac{1}{2}\right\} \\ \left\{\frac{1}{6},2,2\right\} & \left\{\frac{1}{3},4,\frac{1}{6}\right\} & \{1,1,1\} & \left\{\frac{3}{4},\frac{7}{8},\frac{2}{11}\right\} & \left\{\frac{6}{11},7,\frac{6}{11}\right\} \\ \left\{\frac{1}{8},\frac{6}{11},\frac{5}{2}\right\} & \left\{\frac{2}{11},\frac{5}{2},\frac{3}{4}\right\} & \left\{\frac{5}{6},\frac{9}{13},4\right\} & \{1,1,1\} & \left\{\frac{1}{4},\frac{1}{4},\frac{7}{8}\right\} \\ \left\{\frac{2}{7},\frac{2}{11},7\right\} & \left\{\frac{2}{3},\frac{2}{3},\frac{2}{3}\right\} & \left\{1,\frac{1}{8},1\right\} & \left\{3,3,\frac{9}{13}\right\} & \{1,1,1\} \end{bmatrix}. \quad (21)$$

For $a^{1,1}_{1,2}$ = "7/8" in $A^1_{1,2} = \{7/8, 5/6, 3\}$, its upper and lower approximation sets are $\{7/8, 3\}$ and $\{7/8, 5/6\}$. Its rough boundary interval is $RN(a^{1,1}_{1,2}) = [(7/8+5/6)/2, (7/8+3)/2] = [0.8542, 1.9375]$. Meanwhile, $RN(a^{2,1}_{1,2}) = [0.8333, 1.5694]$ and $RN(a^{3,1}_{1,2}) = [1.5694, 3]$. So the rough boundary interval of $A^1_{1,2}$ is $RN(A^1_{1,2}) = [(0.8542+0.8333+1.5694)/3, (1.9375+1.5694+3)/3] = [1.0856, 2.1690]$. The rough boundary interval of other elements in A_1 can be obtained similarly.

The rough judgment matrix can be obtained as $EA_1 = (RN(A^1_{i,j}))_{5\times5}$.

$$EA_1 = \begin{bmatrix} [1,1] & [1.0856, 2.1690] & [0.7407, 2.3704] & [1.2302, 4.5873] & [1.2153, 3.1528] \\ [0.4284, 0.6784] & [1,1] & [1.1019, 3.0185] & [0.8505, 2.7077] & [0.5, 0.5] \\ [0.9815, 1.7963] & [0.6389, 2.5556] & [1,1] & [0.4167, 0.7633] & [1.2626, 4.1313] \\ [0.5057, 1.6932] & [0.5972, 1.7563] & [1.0990, 2.7528] & [1,1] & [0.3194, 0.5972] \\ [0.9683, 4.3773] & [0.6667, 0.6667] & [0.5139, 0.9028] & [1.7179, 2.7436] & [1,1] \end{bmatrix}. \quad (22)$$

EA_1 can be decomposed into the rough lower boundary matrix EA^-_1 and the rough upper boundary matrix EA^+_1, where $EA^-_1 = (a^{-,1}_{i,j})_{5\times5}$ and $EA^+_1 = (a^{+,1}_{i,j})_{5\times5}$.

$$EA^-_1 = \begin{bmatrix} 1 & 1.0856 & 0.7407 & 1.2302 & 1.2153 \\ 0.4284 & 1 & 1.1019 & 0.8505 & 0.5 \\ 0.9815 & 0.6389 & 1 & 0.4167 & 1.2626 \\ 0.5057 & 0.5972 & 1.0990 & 1 & 0.3194 \\ 0.9683 & 0.6667 & 0.5139 & 1.7179 & 1 \end{bmatrix},$$
$$EA^+_1 = \begin{bmatrix} 1 & 2.1690 & 2.3704 & 4.5873 & 3.1528 \\ 0.6784 & 1 & 3.0185 & 2.7077 & 0.5 \\ 1.7963 & 2.5556 & 1 & 0.7633 & 4.1313 \\ 1.6932 & 1.7563 & 2.7528 & 1 & 0.5972 \\ 4.3773 & 0.6667 & 0.9028 & 2.7436 & 1 \end{bmatrix}. \quad (23)$$

Their characteristic vectors corresponding to the maximum eigenvalue are obtained as $VA^-_1 = [-0.5343, -0.3836, -0.4595, -0.3489, -0.4843]^T$ and $VA^+_1 = [-0.5654, -0.3413, -0.4669, -0.3561, -0.4679]^T$.

After averaging, $GA_1 = \{0.5498, 0.3624, 0.4632, 0.3525, 0.4761\}$.

Similarly, $GB_1 = \{0.6237, 0.3994, 0.5608, 0.7786, 0.5672\}$ and $GC_1 = \{0.8911, 0.4718, 0.6601, 0.8593, 0.7709\}$. The values of five cloud service suppliers on the index I_1 are as follows:

$$\begin{aligned} z_{1,1} &= (0.5498, 0.6237, 0.8911), \\ z_{2,1} &= (0.3624, 0.3994, 0.4718), \\ z_{3,1} &= (0.4632, 0.5608, 0.6601), \\ z_{4,1} &= (0.3525, 0.7786, 0.8593), \\ z_{5,1} &= (0.4761, 0.5672, 0.6601). \end{aligned} \quad (24)$$

Using the same method, the value of five cloud service suppliers on other sixteen indexes can be obtained. The triangular fuzzy number index value matrix $Z = (z_{i,t})_{5\times17}$ is shown in Table 1.

By the planning model based on the risk preference, the triangular fuzzy number index value matrix $Z = (z_{i,t})_{5\times17}$ is converted into the real number form $D = (d_{i,t})_{5\times17}$ as shown in Table 2.

After the standardization of $D = (d_{i,t})_{5\times17}$, the index weight vector determined by CRITIC is $\Phi = [0.0767, 0.0042, 0.0993, 0.1092, 0.0794, 0.0886, 0.0869, 0.0459, 0.0767, 0.0200, 0.0826, 0.0037, 0.0324, 0.0054, 0.0114, 0.0963, 0.0813]^T$.

According to the standardized index value matrix $D = (d_{i,t})_{5\times17}$ and the index weight vector Φ, we can get the weighted index value matrix $H = (h_{i,t})_{5\times17}$ as shown in Table 3.

Table 1: The triangular fuzzy number index value matrix $Z = (z_{i,t})_{5\times 17}$ of five cloud service suppliers.

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
1	(0.5498, 0.6237, 0.8911)	(0.1270, 0.6324, 0.8147)	(0.0971, 0.6948, 0.9502)	(0.6463, 0.6797, 0.7547)	(0.1493, 0.8143, 0.8407)	(0.2858, 0.5497, 0.8308)	(0.3371, 0.4694, 0.7943)	(0.8258, 0.9133, 0.9961)	(0.1361, 0.1450, 0.5797)
2	(0.3624, 0.3994, 0.4718)	(0.0975, 0.9058, 0.9134)	(0.1869, 0.4387, 0.7655)	(0.5853, 0.7513, 0.9597)	(0.1966, 0.6160, 0.9293)	(0.0759, 0.5308, 0.9340)	(0.5285, 0.6020, 0.6541)	(0.4427, 0.7749, 0.9619)	(0.0760, 0.5132, 0.6221)
3	(0.4632, 0.5608, 0.6601)	(0.5469, 0.9649, 0.9706)	(0.2760, 0.4456, 0.7094)	(0.2238, 0.2551, 0.3404)	(0.3517, 0.5853, 0.9172)	(0.0119, 0.1622, 0.5688)	(0.1524, 0.2290, 0.5383)	(0.3998, 0.8001, 0.8687)	(0.1839, 0.4173, 0.9027)
4	(0.3525, 0.7786, 0.8593)	(0.1419, 0.4854, 0.9157)	(0.0344, 0.3171, 0.8235)	(0.5060, 0.5472, 0.8909)	(0.2435, 0.2543, 0.2575)	(0.1656, 0.2630, 0.3112)	(0.0046, 0.0782, 0.1067)	(0.1455, 0.5499, 0.8693)	(0.3377, 0.3692, 0.4909)
5	(0.4761, 0.5672, 0.6601)	(0.6787, 0.7431, 0.8491)	(0.3816, 0.4898, 0.7952)	(0.1386, 0.6991, 0.9593)	(0.2511, 0.3500, 0.4733)	(0.0540, 0.1299, 0.7792)	(0.0844, 0.2599, 0.8173)	(0.3510, 0.4018, 0.8530)	(0.0965, 0.2417, 0.7803)

	I_{10}	I_{11}	I_{12}	I_{13}	I_{14}	I_{15}	I_{16}	I_{17}
1	(0.5470, 0.6477, 0.6491)	(0.2963, 0.4509, 0.7317)	(0.3063, 0.5108, 0.4359)	(0.2581, 0.4389, 0.5949)	(0.4886, 0.8010, 0.9289)	(0.0377, 0.3674, 0.9133)	(0.0305, 0.1978, 0.7441)	(0.5005, 0.7127, 0.9787)
2	(0.1320, 0.3897, 0.4039)	(0.1835, 0.1890, 0.6256)	(0.3786, 0.5328, 0.7948)	(0.1707, 0.1948, 0.4357)	(0.2373, 0.5211, 0.9631)	(0.7962, 0.8852, 0.9880)	(0.4799, 0.5000, 0.9047)	(0.0424, 0.0714, 0.6820)
3	(0.0430, 0.2348, 0.8212)	(0.4468, 0.4868, 0.5085)	(0.5502, 0.5870, 0.9390)	(0.1848, 0.9234, 0.9797)	(0.2625, 0.3188, 0.5079)	(0.1068, 0.1366, 0.7212)	(0.6099, 0.6177, 0.8594)	(0.0967, 0.5216, 0.8181)
4	(0.3685, 0.6868, 0.7447)	(0.6443, 0.8116, 0.8176)	(0.2259, 0.2277, 0.8443)	(0.1111, 0.2622, 0.4087)	(0.0292, 0.5785, 0.7303)	(0.4942, 0.6538, 0.7791)	(0.1829, 0.2399, 0.8865)	(0.1499, 0.7224, 0.8175)
5	(0.0154, 0.1690, 0.3532)	(0.3507, 0.6225, 0.8759)	(0.3111, 0.4302, 0.9049)	(0.0855, 0.2967, 0.4242)	(0.2316, 0.4588, 0.5468)	(0.7150, 0.8909, 0.9037)	(0.0287, 0.1679, 0.4899)	(0.4324, 0.4538, 0.8003)

Table 2: The real number form $D = (d_{i,t})_{5\times 17}$.

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	I_{12}	I_{13}	I_{14}	I_{15}	I_{16}	I_{17}
1	0.4631	0.2375	0.2816	0.4800	0.3156	0.2852	0.2671	0.8288	0.0646	0.3766	0.2276	0.1709	0.1763	0.5302	0.1421	0.0712	0.5152
2	0.1681	0.3440	0.1895	0.5743	0.2963	0.2119	0.3525	0.5055	0.1385	0.0878	0.0921	0.3092	0.0647	0.2889	0.7887	0.3762	0.0423
3	0.3119	0.6654	0.2124	0.0734	0.3565	0.0413	0.0815	0.4548	0.2120	0.0933	0.2307	0.4640	0.4250	0.1265	0.0731	0.4773	0.1912
4	0.4165	0.2209	0.1119	0.4054	0.0634	0.0590	0.0032	0.2331	0.1573	0.3467	0.5711	0.1513	0.0611	0.1605	0.4059	0.1486	0.2780
5	0.3196	0.5705	0.2938	0.3068	0.1242	0.0663	0.1114	0.2627	0.1045	0.0244	0.3579	0.2708	0.0634	0.1616	0.6961	0.0379	0.3023

Table 3: The weighted index value matrix $H = (h_{i,t})_{5\times 17}$.

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	I_{12}	I_{13}	I_{14}	I_{15}	I_{16}	I_{17}
1	0.0355	0.0010	0.0280	0.0524	0.0251	0.0253	0.0232	0.0380	0.0050	0.0075	0.0188	0.0006	0.0057	0.0029	0.0016	0.0069	0.0419
2	0.0129	0.0014	0.0188	0.0627	0.0235	0.0188	0.0306	0.0232	0.0106	0.0018	0.0076	0.0011	0.0021	0.0016	0.0090	0.0362	0.0034
3	0.0239	0.0028	0.0211	0.0080	0.0283	0.0037	0.0071	0.0209	0.0163	0.0019	0.0191	0.0017	0.0138	0.0007	0.0008	0.0460	0.0155
4	0.0319	0.0009	0.0111	0.0443	0.0050	0.0052	0.0003	0.0107	0.0121	0.0069	0.0472	0.0006	0.0020	0.0009	0.0046	0.0143	0.0226
5	0.0245	0.0024	0.0292	0.0335	0.0099	0.0059	0.0097	0.0121	0.0080	0.0005	0.0296	0.0010	0.0021	0.0009	0.0079	0.0036	0.0246

Table 4: The calculation process by TOPSIS-CD.

	The connection distance from the object to the positive ideal point	The connection distance from the object to the negative ideal point	The connection distance closeness
S_1	0.1939	0.1782	0.4789
S_2	0.2912	0.1537	0.3455
S_3	0.3536	0.1224	0.2571
S_4	0.4230	0.1195	0.2203
S_5	0.3051	0.1031	0.2525

Table 5: The sorting results of the five suppliers by TOPSIS-CD, TOPSIS [41], TOPSIS-AME [42], and TOPSIS-VP [43].

	TOPSIS-CD		TOPSIS		TOPSIS-AME		TOPSIS-VP	
	Closeness	Sorting order	Closeness	Sorting order	Closeness	Sorting order	Closeness	Sorting order
S_1	0.4789	1	0.5012	1	0.4778	1	0.5032	1
S_2	0.3455	2	0.3988	2	0.4502	2	0.4678	2
S_3	0.2571	3	0.3570	3	0.2445	4	0.4678	2
S_4	0.2203	5	0.1987	5	0.1890	5	0.3089	5
S_5	0.2525	4	0.2456	4	0.3980	3	0.4345	4

The positive ideal point H^+ = [0.0355 0.0028 0.0292 0.0627 0.0283 0.0253 0.0306 0.0380 0.0163 0.0163 0.0075 0.0472 0.0017 0.0138 0.0029 0.0090 0.0460 0.0419], and the negative ideal point H^- = [0.0129 0.0009 0.0111 0.0080 0.0050 0.0037 0.0003 0.0107 0.0050 0.0050 0.0005 0.0076 0.0006 0.0020 0.0007 0.0008 0.0036 0.0034].

The calculation process by TOPSIS-CD is shown in Table 4, so the sorting result is $S_1 > S_2 > S_3 > S_5 > S_4$. The electric power enterprise will select S_1 as its cloud service supplier.

5. Discussion

The sorting results of the five suppliers by TOPSIS-CD, TOPSIS [41], TOPSIS-AME [42], and TOPSIS-VP [43] are listed in Table 5 and compared in Figure 3. The sorting result by TOPSIS-CD is $S_1 > S_2 > S_3 > S_5 > S_4$. The sorting result by TOPSIS is $S_1 > S_2 > S_3 > S_5 > S_4$. The sorting result by TOPSIS-AME is $S_1 > S_2 > S_5 > S_3 > S_4$. The sorting result by TOPSIS-VP is $S_1 > S_2 = S_3 > S_5 > S_4$.

Overall trends of the sorting results by the four methods are generally consistent. The best supplier is S_1 and the worst supplier is S_4. The sorting result of TOPSIS-CD is the same as the result of TOPSIS, so the validity of TOPSIS-CD can be demonstrated. For the obvious insufficiency proved by many scholars, TOPSIS is not desirable.

By TOPSIS-AME, the sorting result of the suppliers S_3 and S_5 is $S_3 < S_5$ which is obviously opposite to the sorting result by the other three methods. By TOPSIS-VP, the suppliers S_2 and S_3 have the equal closeness to ideal points and cannot be sorted. These two methods cannot meet the sorting requirement in some special cases which is consistent with the above analysis in Section 3.4.

Based on the above discussion, the proposed integrated group decision method for cloud service supplier selection mainly has the advantages as follows:

(1) SVM-based classification model is applied for the preliminary screening. The number of candidate suppliers is reduced which can decrease the computation of following algorithm.

(2) TFN-RS-AHP method is designed to calculate supplier's index value which not only can make the most of expert's wisdom and experience but also can reflect the uncertainty of expert judgment.

(3) TOPSIS-CD is put forward to sort the cloud service suppliers by their weighted index value which is better than TOPSIS, TOPSIS-AME, and TOPSIS-VP.

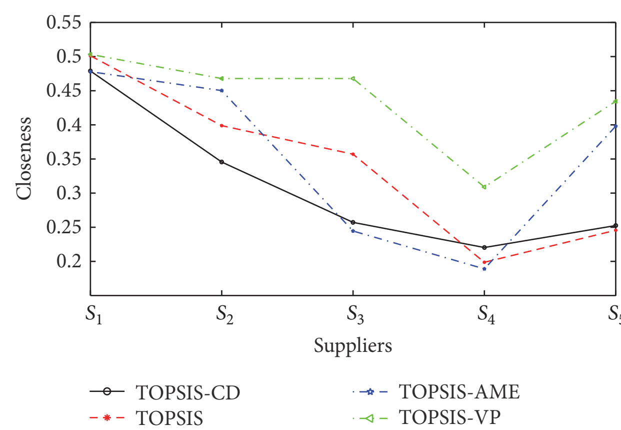

Figure 3: The comparison of the sorting results of the five suppliers by TOPSIS-CD, TOPSIS [41], TOPSIS-AME [42], and TOPSIS-VP [43].

6. Conclusion

With the combination with the new cloud computing technology, many industries are rapidly promoting their information revolution, and the new development mode has emerged now. An important challenge, which enterprise must face, is how to select the best cloud service supplier.

In this paper, the cloud service supplier selection index framework is built from two perspectives of technology and technology management. An integrated group decision method is proposed based on SVM, TFN-RS-AHP, and TOPSIS-CD for cloud service supplier selection. However, a large number of mathematical calculations may exist in the proposed method, and the method may be very cumbersome and complex in the practical application. The subjective preference of expert is still difficult to be represented. In the future, we will focus on the expression and quantification of the preference of expert and the extension and application of the proposed method in other fields.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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