IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 14, 2021, accepted June 14, 2021, date of publication June 17, 2021, date of current version June 28, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3089991

A Practical, Integrated Multi-Criteria Decision-Making Scheme for Choosing Cloud Services in Cloud Systems

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This work was supported in part by the National Social Science Foundation of China under Grant 18XGL010, in part by the National Natural Science Foundation of China under Grant 51974223 and Grant 51774228, in part by the Shaanxi Provincial Natural Science Basic Research Program Joint Fund Project under Grant 2019JLP-16, and in part by the Xi'an Key Laboratory for Intelligent Industrial Perception, Calculation and Decision, Xi'an University of Architecture and Technology under Grant 2019220014SYS015CG037.

ABSTRACT Currently, with the rapid development and broad application of cloud computing technology, companies tend to use cloud services to build their applications or business systems. Selecting a trustworthy cloud service is a challenging multi-criteria decision-making (MCDM) problem. Moreover, decision makers are more inclined to use linguistic descriptions to assess the quality of service (QoS) for cloud services due to the limitation of the decision makers' knowledge and the vagueness of criteria information. Therefore, we propose a practical, integrated MCDM scheme for cloud service evaluation and selection of cloud systems, allowing decision makers to compare cloud services based on QoS criteria. First, to more accurately and effectively express the uncertainty of qualitative concepts, the cloud model is used as a conversion tool for qualitative and quantitative information to quantify linguistic terms. Second, given the shortcomings of traditional differentiating measures between cloud models, a more comprehensive distance measurement algorithm using cloud droplet distribution is proposed for the cloud model. The new distance measurement algorithm is applied to the calculation of cloud model similarity and the gray correlation coefficient. The dynamic expertise weights are determined by calculating the similarity between the expert evaluation cloud model and the arithmetic mean cloud model. Then, we propose a technique for order preference by similarity to an ideal solution (TOPSIS) improved by the grey relational analysis (GRA) to calculate the relative closeness of alternatives to the positive and negative ideal solutions and establish a multi-objective optimization model that maximizes the relative closeness of all alternatives to determine the weights of the criteria. Finally, we reconstructed the QoS evaluation criteria for cloud services from both application and service perspectives, and the classical TOPSIS is applied to generate alternative rankings. The practicability and robustness of the scheme were tested through the cloud service selection problem experienced by a real mining company's scheduling platform, which can provide practical references with the theoretical basis for the selection and evaluation of cloud services.

INDEX TERMS Cloud services selection, quality of service (QoS), cloud model, multi-criteria decision-making (MCDM), technique for order preference by similarity to an ideal solution (TOPSIS), grey relational analysis (GRA).

I. INTRODUCTION

With the development and widening application of Internet technology as well as the demands created by modern big data collection, the demand for more powerful Internet data processing capabilities is increasing, and "cloud computing" technology has gradually become the focus of the computer technologies field [1], [2]. Cloud computing integrates many computing resources, storage resources, and software resources through information technologies such as

The associate editor coordinating the review of this manuscript and approving it for publication was Mahmoud Elish.

distributed computing, utility computing, parallel computing, grid computing, and virtualization, forming a colossal virtual shared resource pool to provide users with the information they need [3]–[5]. The services performed by cloud computing are called cloud services, and the National Institute of Standards and Technology (NIST) defines cloud services as a ubiquitous, convenient, and on-demand mode of network access to a configurable shared computing resource [6]. Cloud services can achieve rapid supply and release of resources such as computing networks, servers, hardware, and software through minimal management or interaction with service providers [7]. Cloud services have the characteristics of low initial investment, low technical requirements for personnel, short deployment time, easy expansion, and additionally, customers do not need to be aware of the internal structure of cloud services and actual service methods. Relying on the advanced service concept of cloud computing, enterprises or individual users tend to use cloud services to build their business systems or personal applications and establish new development models.

When users decide to adopt cloud services, a significant problem they face is the selection of the best cloud service technology [8]. Per the user's requirements, cloud computing architecture primarily provides three services: Software-as-a-Service (SaaS), Platform-as-a-Service (PaaS), and Infrastructure-as-a-Service (IaaS) [9]. These three services are usually referred to as SPI models. Cloud computing forms can be divided into private cloud, public cloud, and hybrid cloud. References [10]. In recent years, with the rapid growth in cloud computing, users have expanded their demand for cloud service applications, and various cloud services continue to emerge. Selecting the cloud service that best suits the needs of users should consider multiple criteria [11]. Thus, the selection of cloud services can be viewed as a multi-criteria decision-making (MCDM) problem. Currently, scholars have put forward many evaluation criteria for quality of service (QoS) [12]–[14]. However, these criteria only focus on the real-time characteristics of cloud services or simply treat the characteristics as an average value [15]. The former does not consider the historical characteristics of QoS, resulting in excessive partiality and ignorance of holistic performance, while the latter ignores the frequent updates of QoS characteristics, which is not representative. The specific QoS value cannot truly reflect the dynamic changes of cloud services, nor does it consider the subjective factors of users, and cannot fully reflect the value a user' would get from the service. To this end, we construct the QoS criteria for cloud services from the perspectives of application and management, and use vague language terms to evaluate the QoS of cloud services, which can more truly reflect the user cloud service experience.

Due to the differences in the industry background as well as differences in the perception of the cloud QoS criteria of among decision makers, their evaluation language contains various uncertain information. Therefore, a systematic method for dealing with the uncertainty in the quantitative conversion of linguistic information is an essential factor that affects the validity and accuracy of decision-making results. Zadeh and Lotfi [16] proposed the fuzzy set theory and established a membership function as the primary tool for processing uncertain information. The application of fuzzy set theory is constantly improving and expanding. Considering that most natural and social phenomena obey or approximately obey the law of normal distribution, Jean and Saade [17] proposed the concept of normal fuzzy sets. Ma [18] proposed using normal fuzzy numbers to express decision-making information, which more objectively and accurately describes and reflects the data in the real world. Intuitionistic Fuzzy Set (IFS) proposed by Atanassov [19] is an attractive tool for dealing with data ambiguity and inaccuracy. Yager [20] proposed that the Pythagorean Fuzzy Set (PFS) can be considered a useful extension of IFS. Zeng *et al.* [21] supplemented the powerful PFS with confidence levels to represent information in the decision-making process concerning low-carbon supplier evaluation, considering the different confidence levels decision makers use when addressing vagueness and imprecision. However, uncertainty includes two components: fuzziness and randomness. If uncertainty appears but is difficult to define accurately, it is called fuzziness. When an event is clearly defined, but the uncertainty involved may or may not appear, that uncertainty is called randomness. Previous studies reflect only the uncertainty of qualitative concepts from the perspective of fuzziness, failing to consider the randomness of membership. Given this, Li *et al.* [22] proposed the concept of the cloud model, unifying the problem of ambiguity and the randomness of membership, which better portrays the uncertainty of concepts in natural language. Li *et al.* [23] further demonstrated the universality of the normal cloud model. Du *et al.* [24] researched the mapping method for qualitative and quantitative variables based on the cloud model, which retained the inherent uncertainty in the evaluation process to the greatest extent and improved the credibility of the evaluation results.

A method for determining the weights of decision-makers and criteria in ranking and selecting alternatives is the core issue. In the process of traditional technology evaluation, decision makers' weights are often directly given values, and criteria weights are usually directly given or assigned by decision makers, and thus are highly subjective [25]–[27]. However, due to the ambiguity and limitations of the objective environment, decision-makers have limited information processing capabilities [28], [29]. Decision-makers can only provide a set of constrained or incomplete weight information, and it is impossible to assign precise weights to each indicator [30]. Therefore, considering the lack of given decision maker and criteria weights, it is necessary to determine the weights more objectively by making calculations during the decision-making process [31]–[33]. Liu [34] proposed a new similarity function as weight support, which has good reliability and accuracy. Zhang *et al.* [35] proposed a grey relational analysis method and a maximum deviation method to calculate both expert and criteria weight information.

Zeng *et al.* [36] extends the improved induced weighted logarithmic distance measurement algorithm to q-ROFS and proposes a new method for processing entirely unknown criteria weight information in a q-ROFS environment. Qin *et al.* [37] used the similarity between the evaluation value and the average to calculate the expert weight and index weight from different angles, where the similarity was determined based on the distance between the evaluation value and the average. From the above research, it is not difficult to see that measuring the similarity and difference in evaluation information between decision-makers is the key to calculating the weights for decision makers and for criteria. Therefore, calculating the distance and similarity between cloud models to express decision maker evaluation information is the critical problem, and the solution to this problem will provide a solution for weight calculation [38], [39]. Zhao *et al.* [40] defined the Hamming distance between two normal cloud models and proposed a cloud distance measurement algorithm.

Considering that the cloud model comprises a particular random rule and many cloud drops, even the cloud models with the same digital characteristics have different cloud drops. Measuring the distance and similarity between cloud models based on digital features, ignoring the essential characteristics of cloud model fuzziness and randomness, produces calculation results that are not reliable or accurate. Therefore, we propose a more comprehensive cloud model distance and similarity measurement algorithm from the perspective of cloud droplet distribution. The dynamic expert weights are determined by calculating the similarity between the expert evaluation cloud model and the arithmetic mean cloud model. In addition, we determine the weights of criteria based on the principle of optimizing the comprehensive evaluation of all alternatives. The technique for order preference by similarity to an ideal solution (TOPSIS) is a commonly used method in MCDM. It positions alternatives close to the positive ideal solution and at the same time, further from the negative ideal solution [41]. The closeness calculation in the TOPSIS method is a simple weighted average of the score difference between the alternative and the ideal solution for each criterion. However, when solving the criteria weights, the difference between the alternatives' criterion scores should be consistent with the ideal solution. Lessons can also be drawn from grey relational analysis (GRA) [42], as it can flexibly measure the similarity of curve shapes and visually represent the nonlinear relationship between data sequences. The closer the curve shapes are, the higher the degree of correlation between the sequences. The GRA method is used to solve the relative closeness to improve TOPSIS so that the approximate distance and correlation degree between the alternative and the ideal solution can be considered simultaneously. Therefore, we established a multi-objective optimization model that maximizes the relative closeness of all alternatives through TOPSIS improved by GRA, to determine the optimal index weights more accurately, objectively, and reasonably.

This article aims to propose a practical, integrated MCDM scheme based on cloud systems to evaluate and select cloud services within a linguistic environment based on the discussions above. The main contributions of this research are summarized as follows: first, the linguistic information given by the decision maker is converted into the corresponding cloud model, which can manage the ambiguity and randomness of language expression; second, we propose an algorithm to measure the distance and similarity of cloud models from the perspective of cloud drop distribution and determine the dynamic decision maker weights by calculating the distance and similarity between the decision maker's cloud model and the arithmetic average cloud model; third, we propose to use GRA to improve the TOPSIS method and establish a multi-objective optimization model that maximizes the relative closeness of all alternatives to determine the optimal criteria weights; fourth, we use the cloud distance measurement algorithm and the TOPSIS method to calculate the relative closeness of alternatives and rank the alternatives according to the relative closeness; finally, the proposed MCDM scheme is applied to the decision-making of truck dispatching cloud service used by the Luanchuan Mining Group Corporation, which illustrates the practicality and robustness of the proposed MCDM scheme.

The rest of this article is structured as outlined below: Section 2 introduces some basic concepts related to cloud model theory. Section 3 proposes an MCDM scheme for Cloud Service Evaluation and Selection. Section 4 applies the proposed method to engineering practice and conducts a comparative study and sensitivity analysis. Finally, Section 5 discusses conclusions and directions for further research.

II. PRELIMINARIES

The cloud model is proposed by Li *et al.* [22] to transform the linguistics of qualitative concepts into quantitative conversion models. In this section, definitions 1-5 are the basic concepts and operations related to cloud model theory, and Definitions 6-7 are the conversion methods for transforming Linguistic terms into cloud models.

Definition 1: Assuming a domain $U = \{X\}$, A is a qualitative concept related to U, and the membership degree $\mu_{A(x)} \in [0, 1]$ of the element X in U to the qualitative concept of T is a stable tendency. The distribution of the membership degree x on the universe U is called a cloud, and each random number is called a cloud drop [23].

Definition 2: Three parameters depict the characteristics of a cloud y: expected value Ex, entropy En, and hyper-entropy He. Here, Ex is the expected value of the cloud drop, which represents the central value of the universe, the entropy En measures the fuzziness and randomness of the qualitative concepts, and He reflects the dispersion degree of the cloud drops and the uncertainty of the membership function. Generally, a cloud y can be expressed as $y = (Ex, En, He)$ [23].

When the number of cloud drops $n = 1000$, the cloud model $C_1 = (0.3, 0.1, 0.01)$, $C_2 = (0.5, 0.1, 0.01)$, $C_3 = (0.5, 0.05, 0.005)$ and $C_4 = (0.7, 0.05, 0.005)$ can be

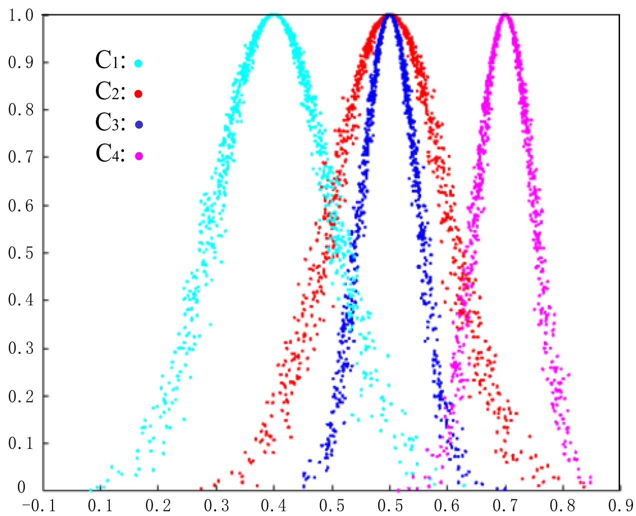

FIGURE 1. **Comparison diagram of different cloud models.**

represented as a cloud diagram comparison chart, as shown in Figure 1. The expected value *Ex* of C_2 and C_3 is the same, so the cloud image's position center is the same. The entropy *En* and hyper-entropy *He* of C_2 are larger than that of C_3, so the cloud image of C_2 has a larger span and thickness. The entropy *En* and hyper-entropy *He* of C_1 and C_2 are the same, and the entropy *En* and the hyper-entropy *He* of C_3 and C_4 are the same. The expected value *Ex* of C_1 is the smallest, which means that the expected value of its qualitative concept is the smallest, and therefore its position is more to the left in the figure. The expected value *Ex* of C_4 is the largest, which means that the expected value of its qualitative concept is the largest, and therefore it is more to the right in the figure.

Definition 3: Assuming any two clouds $\tilde{y}_1 = (Ex_1, En_1, He_1)$ and $\tilde{y}_2 = (Ex_2, En_2, He_2)$ in a given universe U, the algebraic operations between the two clouds is expressed as Equation (1-4).

$$\tilde{y}_1 + \tilde{y}_2 = \left(Ex_1 + Ex_2, \sqrt{En_1^2 + En_2^2}, \sqrt{He_1^2 + He_2^2}\right) \tag{1}$$

$$\tilde{y}_1 \times \tilde{y}_2 = \left(Ex_1Ex_2, \sqrt{(En_1Ex_2)^2 + (En_2Ex_1)^2}, \sqrt{(He_1Ex_2)^2 + (He_2Ex_1)^2}\right) \tag{2}$$

$$\lambda\tilde{y}_1 = \left(\lambda Ex_1, \sqrt{\lambda}En_1, \sqrt{\lambda}He_1\right), \lambda > 0 \tag{3}$$

$$\tilde{y}_1^{\lambda} = \left(Ex_1^{\lambda}, \sqrt{\lambda}(Ex_1)^{\lambda-1}En_1, \sqrt{\lambda}(Ex_1)^{\lambda-1}He_1\right), \lambda > 0 \tag{4}$$

Definition 4: Assuming that $\tilde{y}_1 = (Ex_1, En_1, He_1)$ and $\tilde{y}_2 = (Ex_2, En_2, He_2)$ are any two clouds in a given universe U, then the pseudo-code of the distance measurement algorithm between the cloud models is as follows.

If the number of cloud drops that are filtered out is inconsistent, fewer cloud drops are included in the unified number

Algorithm 1 The Algorithm of Cloud Model Distance Measurement

Input: Two cloud models $\tilde{y}_1 = (Ex_1, En_1, He_1)$ and $\tilde{y}_2 = (Ex_2, En_2, He_2)$ and the number of cloud drops n.
Output: The distance between two cloud models $d(\tilde{y}_1, \tilde{y}_2)$

1: Generate n cloud drops using a forward cloud generator. $\tilde{y}_1$ and $\tilde{y}_2$ each generate n cloud drops, which are denoted as: $(x_{1i}, u(x_{1i}))$; $(x_{2i}, u(x_{2i}))$, $i = 1, 2, \ldots, n$
2: Sort the two groups of cloud drops in ascending order according to the value of x_{1i} and x_{2i}
3: Select x_{1i} and x_{2i} to meet the cloud drop in the following interval: $[max\{X_{min}, Ex_1 - 3En_1\}, min\{X_{max}, Ex_1 + 3En_1\}]$, $[max\{X_{min}, Ex_1 - 3En_1\}, min\{X_{max}, Ex_1 + 3En_1\}]$. The number of cloud drops are denoted as n_1 and n_2
4: **if** $n_1 \geq n_2$
5: **then** Randomly select n_2 cloud drops from n_1 and store them in set $Drop_1$
6: **else** Randomly select n_1 cloud drops from n_2 and store them in set $Drop_2$
7: **end if**
8: $K \leftarrow \min\{n_1, n_2\}$
9: **for** $j \leftarrow 1$ to k **do**
10: Calculate the distance between each cloud drop $D\left(drop_{1j}, drop_{2j}\right) = \sqrt{\left(x_{1j} - x_{2j}\right)^2 + \left(\mu(x)_{1j} - \mu(x)_{2j}\right)^2}$
11: Calculate the distance between each cloud model $= \sum_{j=1}^{k} D\left(drop_{1j}, drop_{2j}\right)/k$
12: **end for**
13: **return**: $d(\tilde{y}_1, \tilde{y}_2)$

of cloud drops (line 4-7). That is because according to the "***3σ***" rule, the number of cloud drops with the abscissa in the range of [*Ex-3En*, *Ex+3En*] accounts for most of the total number of cloud drops. The difference between the number of filtered clouds drops n_1 and n_2 can be ignored so that the excess cloud drop can be discarded directly [43], [44]. The distance between the two cloud models is equal to the average distance between the cloud drops filtered by the two cloud models (line 8-12). Additionally, due to the randomness of cloud droplet distribution, the distance calculation result also has a certain degree of randomness [45]. The cloud model distance measurement algorithm fully measures the distribution difference of each cloud drop in different cloud models. This algorithm is more global than calculating the distance between cloud models through the three numerical features *Ex*, *En*, and *He*.

Definition 5: Suppose there are n clouds $\tilde{y}_i = (Ex_i, En_i, He_i)$ $(i = 1, 2, \ldots, n)$ in the universe U, and $w = (w_1, w_2, \ldots, w_n)$ is the corresponding weight. Calculate the weighted cloud $Y(Ex, En, He)$ using the integrated function as shown as Equation (5) [46].

$$\begin{cases} Ex = \omega_1 Ex_1 + \omega_2 Ex_2 + \cdots + \omega_x Ex_n, \\ En = \sqrt{(\omega_1 En_1)^2 + (\omega_2 En_2)^2 + \cdots + (\omega_x En_n)^2}, \\ He = \sqrt{(\omega_1 He_1)^2 + (\omega_2 He_2)^2 + \cdots + (\omega_n He_n)^2}. \end{cases} \tag{5}$$

In particular, when the weight of each cloud model is equal $w_i = \frac{1}{n(i=1,2,\ldots,n)}$, the weighted cloud after n cloud models is superimposed and called the arithmetic mean cloud, denoted as $\overline{Y}\left(\overline{E}x, \overline{E}n, \overline{H}e\right)$, The integration method is shown in Equation (6).

$$\begin{cases} \overline{E}x = (Ex_1 + Ex_2 + \cdots + Ex_n)/n, \\ \overline{E}n = \sqrt{En_1^2 + En_2^2 + \cdots + En_n^2/n}, \\ \overline{H}e = \sqrt{He_1^2 + He_2^2 + \cdots + He_n^2/n}. \end{cases} \tag{6}$$

Definition 6: Assuming that $[X_{min}, X_{max}]$ is a valid domain, $S = \{s_{-g}, \ldots, s_0, \ldots, s_g, g \in N\}$ is an ordered discrete term set, where N represents a non-negative integer and s_i represents a linguistic term, that can generate $2g + 1$ clouds, denoted as $\tilde{y}_g = (Ex_{-g}, En_{-g}, He_{-g}), \ldots, \tilde{y}_0 = (\mathrm{Ex}_0, \mathrm{En}_0, \mathrm{He}_0), \ldots, \tilde{y}_g = (Ex_g, En_g, He_g)$ [47].

Definition 7: Given the linguistic terms set $S = \{s_{-g}, \ldots, s_0, \ldots, s_g, g \in N\}$, the transformation function from S_i to cloud Y_i [48], is given by

$$Y_i = \begin{cases} \dfrac{a^g - a^{-i}}{2a^g - 2}, & -g \leqslant i \leqslant 0 \\ \dfrac{a^g + a^i - 2}{2a^g - 2}, & 0 \leqslant i \leqslant g \end{cases} \tag{7}$$

where the interval of a is in [1.36, 1.40].

III. THE PROPOSED MCDM SCHEME FOR CLOUD SERVICE EVALUATION AND SELECTION

This section combines the cloud model with the improved TOPSIS method and introduces a practical integrated MCDM scheme to solve for uncertain criterion information and unknown weight information in cloud service evaluation and selection. The MCDM scheme proposed in this paper includes three stages: phase 1, evaluation of the cloud service QoS, and translation of linguistic terms into cloud models; phase 2, use of cloud similarity to determine dynamic expert weights and use of multi-objective optimization models to determine the weights of the QoS criteria for cloud services; phase 3, determination of the alternative cloud service ranking order. The procedure of the proposed MCDM scheme is shown in Figure 2.

A. ASSESS THE CLOUD SERVICE QoS

Suppose that the alternative cloud service is $A_i (1 \leqslant i \leqslant m)$, and the criterion is $C_j (1 \leqslant j \leqslant n)$ in the cloud service QoS evaluation problem. A decision-making group consisting of k experts $E_t (1 \leqslant t \leqslant k)$ uses linguistic terms to evaluate the QoS for alternative cloud services.

Step 1 (Obtain the Cloud Model Decision Matrix): According to the method for converting linguistic terms into cloud models, the expert's linguistic term evaluation matrix for the cloud services' QoS $E_k = [E_{ijk}]_{m\times n}$ is transformed into cloud model decision matrix $Y_k = [y_{ijk}]_{\mathrm{m}\times\mathrm{n}}$ where $y_{ijk} = (Ex_{ijk}, En_{ijk}, He_{ijk})$.

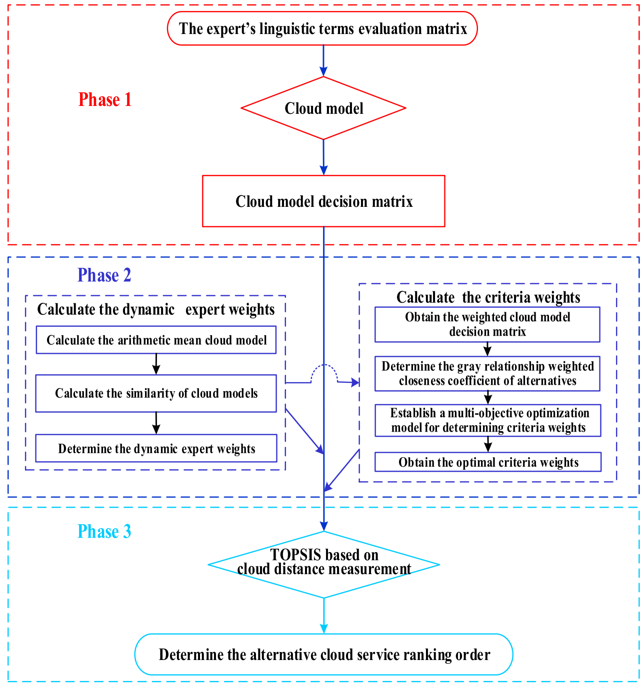

FIGURE 2. Flowchart of the proposed MCDM scheme.

B. CALCULATE THE WEIGHTS OF EXPERTS AND CRITERIA

1) CALCULATE THE DYNAMIC EXPERT WEIGHTS

Different cloud services or different criteria for QoS often correspond to different expert weights, called dynamic expert weights and recorded as v_{ij}^t. This section determines the dynamic expert weights based on the similarity between the cloud models given by the expert E_t and the arithmetic mean cloud of the expert group. The smaller the similarity, the smaller the weight of the corresponding expert E_t, and vice versa. The calculation steps are as follows.

Step 2 (Calculate the Arithmetic Mean Cloud Model): Using Equation (6) to calculate the criterion C_j for cloud service A_i, the arithmetic mean cloud model $\overline{y}_{ij} = \left(\overline{E}x_{ij}, \overline{E}n_{ij}, \overline{H}e_{ij}\right)$ is given by k experts after cloud model integration.

$$\begin{cases} \overline{E}x_{ij} = \left(Ex_{ij}^1 + Ex_{ij}^2 + \cdots + Ex_{ij}^k\right)/k, \\ \overline{E}n_{ij} = \sqrt{En_{ij}^1 + En_{ij}^2 + \cdots + En_j^k/k}, \\ \overline{H}e_{ij} = \sqrt{He_{ij}^1 + He_{ij}^2 + \cdots + He_{ij}^k/k}. \end{cases} \tag{8}$$

Step 3 (Determine the Dynamic Expert Weights): Calculate the similarity between the evaluation cloud model y_{ij}^t and the arithmetic mean cloud model $\tilde{y}_{ij}$ by Equation (9).

$$sim\left(y_{ij}^{t}, \bar{y}_{ij}^{t}\right) = 1 - \frac{d\left(y_{ij}^{t}, \bar{y}_{ij}^{t}\right)}{\sum_{i=1}^{k} d\left(y_{ij}^{t}, \bar{y}_{ij}^{t}\right)} \tag{9}$$

where $d(y_{ij}^{t}, \bar{y}_{ij}^{t})$ is the distance between the evaluation cloud model y_{ij}^{t} and the arithmetic mean cloud model $\bar{y}_{ij}^{t}$ calculated by Algorithm 1.

Using Equation (10), calculate the dynamic expert weights corresponding to the QoS criterion C_j of cloud service A_i

$$v_{ij}^{t} = \frac{sim\left(y_{ij}^{t}, \bar{y}_{ij}^{t}\right)}{\sum_{t=1}^{k} sim\left(y_{ij}^{t}, \bar{y}_{ij}^{t}\right)}, \quad t = 1, 2, \ldots, k \tag{10}$$

2) CALCULATE THE CRITERIA WEIGHTS

Drawing lessons from GRA, we use it to solve for the relative closeness of alternatives to improve TOPSIS. In addition, we establish a multi-objective optimization model to maximize the relative closeness of alternatives and then determine the optimal criteria weights by finding a solution to the model. Figure 3 shows the calculation used to find the criteria weights.

Step 4 (Obtain the Weighted Cloud Model Decision Matrix): Using Equation (5) to gather the evaluation cloud model y_{ij}^{t} of the cloud services' QoS by multiple experts, and obtain the weighted cloud model $\hat{y}_{ij}$, where $\hat{y}_{ij} = \left(\hat{E}x_{ij}, \hat{E}n_{ij}, \hat{H}e_{ij}\right)$, and its constituents are given by

$$\begin{cases} \hat{E}x_{ij} = v_{ij}^{1}Ex_{ij}^{1} + v_{ij}^{2}Ex_{ij}^{2} + \cdots + v_{ij}^{k}Ex_{ij}^{k} \\ \hat{E}n_{ij} = \sqrt{\left(v_{ij}^{1}En_{ij}^{1}\right)^{2} + \left(v_{ij}^{2}En_{ij}^{2}\right)^{2} + \cdots + \left(v_{ij}^{k}En_{ij}^{k}\right)^{2}} \\ \hat{H}e_{ij} = \sqrt{\left(v_{ij}^{1}He_{ij}^{1}\right)^{2} + \left(v_{ij}^{2}He_{ij}^{2}\right)^{2} + \cdots + \left(v_{ij}^{k}He_{ij}^{k}\right)^{2}} \end{cases} \tag{11}$$

where v_{ij}^{t} $(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; t = 1, 2, \ldots, k)$ are the dynamic expert weights.

All weighted cloud models y_{ij} constitute a weighted cloud model decision matrix $\hat{Y}_k = (\hat{y}_{ij})_{m\times n}$, namely

$$\hat{Y}_k = \begin{bmatrix} \hat{y}_{11} & \hat{y}_{12} & \cdots & \hat{y}_{1n} \\ \hat{y}_{21} & \hat{y}_{22} & \cdots & \hat{y}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{y}_{m1} & \hat{y}_{m2} & \cdots & \hat{y}_{mn} \end{bmatrix} \tag{12}$$

Step 5 (Determine the Relative Closeness of Alternatives): The positive-ideal cloud model $\hat{y}_j^{+}$ and the negative-ideal cloud model $\hat{y}j^{-}$ used to determine cloud service QoS is shown in Equation (13).

$$\begin{cases} \hat{y}_j^{+} = \left\{max\hat{y}_{ij} \mid i = 1, 2, \cdots, m\right\} \\ \hat{y}_j^{-} = \left\{min\hat{y}_{ij} \mid i = 1, 2, \cdots, m\right\} \end{cases} \tag{13}$$

$\hat{y}_j^{+}$ and $\hat{y}_j^{-}$ are the gray relational coefficients of the alternatives with respect to the positive and negative ideal solutions,

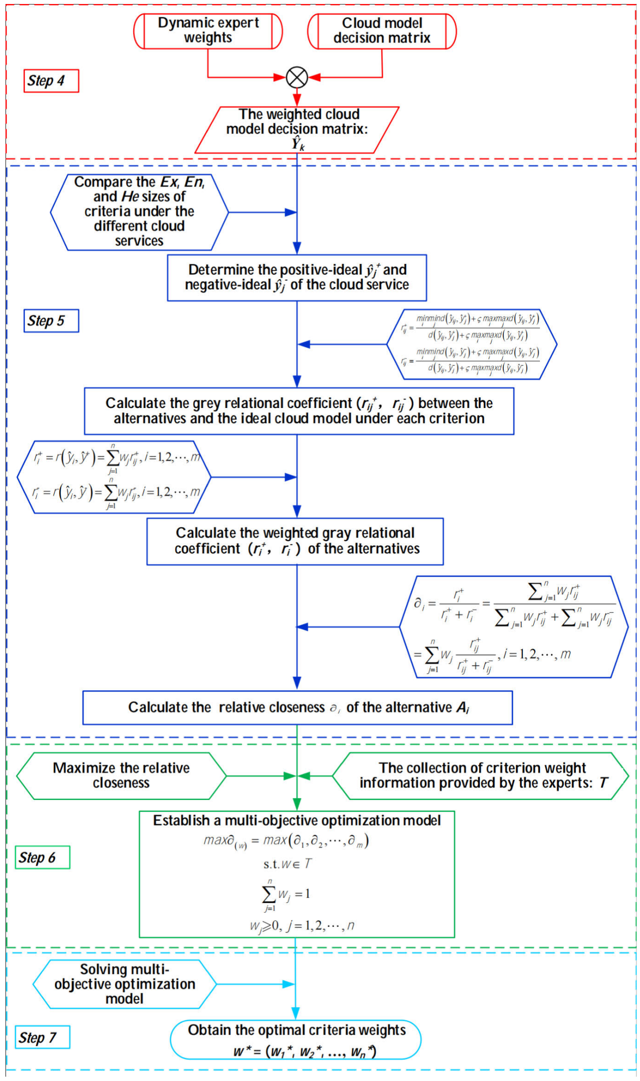

FIGURE 3. Calculation steps for finding criteria weights.

given by

$$r_{ij}^{+} = \frac{\min\limits_{i}\min\limits_{j} d\left(\hat{y}_{ij}, \hat{y}_j^{+}\right) + \varsigma \max\limits_{i}\max\limits_{j} d\left(\hat{y}_{ij}, \hat{y}_j^{+}\right)}{d\left(\hat{y}_{ij}, \hat{y}_j^{+}\right) + \varsigma \max\limits_{i}\max\limits_{j} d\left(\hat{y}_{ij}, \hat{y}_j^{+}\right)} \tag{14}$$

$$r_{ij}^{-} = \frac{\min\limits_{i}\min\limits_{j} d\left(\hat{y}_{ij}, \hat{y}_j^{-}\right) + \varsigma \max\limits_{i}\max\limits_{j} d\left(\hat{y}_{ij}, \hat{y}_j^{-}\right)}{d\left(\hat{y}_{ij}, \hat{y}_j^{-}\right) + \varsigma \max\limits_{i}\max\limits_{j} d\left(\hat{y}_{ij}, \hat{y}_j^{-}\right)} \tag{15}$$

where $i = 1, 2, \ldots, m$; $j = 1, 2, \cdots, n$; $d(\hat{y}_{ij}, \hat{y}_j^{+})$ and $d(\hat{y}_{ij}, \hat{y}_j^{-})$ represent the gray relational coefficients from $\hat{y}_{ij}$ to $\hat{y}_j^{+}$ and $\hat{y}_j^{-}$, respectively. ς is the resolution coefficient, usually $\varsigma = 0.5$.

We then calculate the weighted grey relational coefficients for the alternatives using the following equations.

$$r_i^{+} = r\left(\hat{y}_i, \hat{y}^{+}\right) = \sum_{j=1}^{n} w_j r_{ij}^{+}, \quad i = 1, 2, \cdots, m \tag{16}$$

$$r_i^- = r\left(\hat{y}_i, \hat{y}^-\right) = \sum_{j=1}^{n} w_j r_{ij}^-, \quad i = 1, 2, \cdots, m \tag{17}$$

Then, we calculate the relative closeness of alternative A_i using Equation (18):

$$\begin{aligned} \partial_i &= \frac{r_i^+}{r_i^+ + r_i^-} = \frac{\sum_{j=1}^{n} w_j r_{ij}^+}{\sum_{j=1}^{n} w_j r_{ij}^+ + \sum_{j=1}^{n} w_j r_{ij}^-} \\ &= \sum_{j=1}^{n} w_j \frac{r_{ij}^+}{r_{ij}^+ + r_{ij}^-}, \quad i = 1, 2, \cdots, m \end{aligned} \tag{18}$$

Step 6 (Establish a Multi-Objective Optimization Model for Determining Optimal Criteria Weights): Set $w = (w_1, w_2, \ldots, w_j, \ldots, w_n)$ to be the vector of necessary weights and solve the following linear programming problem to obtain the optimal weights.

$$\begin{aligned} max\,\partial_{(w)} &= max\,(\partial_1, \partial_2, \cdots, \partial_m) \\ &\text{s.t.} \sum_{j=1}^{n} w_j = 1 \\ &\quad w_j \geqslant 0, \quad j = 1, 2, \cdots, n \end{aligned} \tag{19}$$

If the experts give information about the criteria weights, add corresponding conditions to the constraints. Assuming that T is a collection of weight information given by the experts, it can include the following forms:

1. Weak order: $\{w_i \geq w_j\}$;
2. Strict order: $\{w_i - w_j\} \geq \delta_i | \delta_j > 0\}$;
3. Order of multiples: $\{w_i \geq \delta_i w_j\}$;
4. Interval order: $\{\delta_i \leq w_i \leq \delta_i + \varepsilon i | 0 \leq \delta_i \leq \delta_i + \varepsilon_i \leq 1\}$;
5. Difference order: $\{w_i - w_j \geqslant w_k - w_l | j \neq k \neq l\}$.

Then the following multi-objective optimization model can be established.

$$\begin{aligned} max\,\partial_{(w)} &= max\,(\partial_1, \partial_2, \cdots, \partial_m) \\ &\text{s.t. } w \in T \\ &\quad \sum_{j=1}^{n} w_j = 1 \\ &\quad w_j \geqslant 0, \quad j = 1, 2, \cdots, n \end{aligned} \tag{20}$$

Step 7 (Obtain the Optimal Criteria Weights): By executing the multi-objective optimization model, the optimal criteria weights can be obtained as $w^* = (w_1^*, w_2^*, \ldots, w_n^*)$.

C. DETERMINE THE RANKING OF ALTERNATIVES

The distance measurement algorithm for the cloud model is applied to the TOPSIS method, and the closeness of the alternative cloud service's QoS is calculated according to the optimal weighted cloud decision matrix $\hat{Z}_k$, and then the alternative cloud service's QoS is ranked according to the closeness. Specific steps are as follows.

Step 8 (Calculate the Optimally Weighted Cloud Decision Matrix): The expert's dynamic weight v_{ij}^k and criteria's optimal weight w_j^* are respectively multiplied with each element y_{ij} in the jth column of the cloud model decision matrix Y_k to obtain the optimally weighted cloud decision matrix $\hat{Z}_k$ as Equation (21).

$$\hat{Z}_k = \left[\hat{z}_{ij}\right]_k^{m \times n} = \sum_{k=1}^{t} v_{ij}^k \cdot \left[w_j^* \cdot y_{ij}\right]_k^{m \times n} \tag{21}$$

Step 9 (Determine the Positive-Ideal and the Negative-Ideal Solutions): Within the optimally weighted cloud model decision matrix $\hat{Z}_k$, the positive-ideal solution and the negative-ideal solution denoted as $\hat{Z}_k^+$ and $\hat{Z}_k^-$, can be respectively calculated by

$$\hat{Z}_k^+ = \left\{\hat{z}_j^+ | \max_{1 \leqslant i \leqslant m} \hat{z}_{ij}\right\} \tag{22}$$

$$\hat{Z}_k^- = \left\{\hat{z}_j^- | \min_{1 \leqslant i \leqslant m} \hat{z}_{ij}\right\} \tag{23}$$

where $max\hat{z}_{ij}$ represents the expectation that $Ex_{ij}(i = 1, 2, \ldots, m)$ is the largest and $min\hat{z}_{ij}$ means that the expectation $Ex_{ij}(i = 1, 2, \ldots, m)$ is the smallest. When the ideal solution has the same expectation, then En_{ij} and He_{ij} are the smallest.

Step 10 (Calculate the Distance Between the Alternatives and the Ideal Solution): Calculate the distance between the alternative A_i and the ideal solution through algorithm 1 and the following equations.

$$D_i^+ = \sum_{j=1}^{n} d\left(\hat{z}_{ij}, \hat{z}_j^+\right) \tag{24}$$

$$D_i^- = \sum_{j=1}^{n} d\left(\hat{z}_{ij}, \hat{z}_j^-\right) \tag{25}$$

Step 11 (Calculate the Relative Closeness of the Alternatives and Rank the Alternatives): Calculate the relative closeness G_i of the QoS of cloud service A_i using Equation (26):

$$G_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{26}$$

The cloud services' QoS is ranked according to the value of G_i. The larger the G_i value is, the higher the QoS of the corresponding cloud service.

IV. PERFORMANCE ANALYSIS AND ENGINEERING APPLICATIONS

We apply the proposed method to the cloud service selection of a real mining company's truck dispatch platform. The applicability and efficacy of the proposed MCDM scheme for cloud service evaluation and selection are demonstrated in this section.

A. BACKGROUND DESCRIPTION

With the continuous development of industrialization and informatization, the current development direction of the mining industry is focused on green development, intelligent mining, driving the development of information technology, and accelerating the development of modern mining. The high degree of mechanization of open-pit mining facilitates the adoption of new technologies in the information age to realize automated mining, so its development of industrialization and informatization has become a trend. As the primary information age management method, cloud services have become the best solution for enterprise information integration, information resource development and decision support systems. In addition, a new model for integrating mined resources has been developed.

In this study, we considered the Luanchuan Molybdenum Group Company, located in Luoyang, China. In order to rationally deploy open-pit mine transportation operations, intelligently dispatch and manage vehicles, and realize big data-driven, intelligent decision-making analysis, the company is supported by big data technology and uses cutting-edge technologies such as GPS, Google Maps and 5G networks to realize the transmission and display of various production information. The company uses JavaWeb as a development method for designing an intelligent dispatching system for open-pit mines under a cloud service model, and uses cloud services to gather information resources such as open-pit mine production and transportation data to form a resource pool.

The selection of evaluation criteria is an important basis for evaluating the cloud service QoS. In 2012, the International Cloud Service Measurement Alliance (ICSMA) designed and released the cloud service evaluation criteria to evaluate cloud services from seven aspects: performance, security and privacy, price, availability, responsibility, agility and insurance [49]. MCDM methods based on these criteria have gradually become the mainstream for cloud computing evaluation [50], [51]. Although the above studies provide cloud service evaluation criteria and methods from an application perspective, different vendors can provide similar or identical cloud services, and the choice of vendors is inherently related to the application's industry. Therefore, when choosing cloud services, the evaluation criteria for cloud services should be constructed from both the application and management perspectives. According to literature surveys [11], [52], the opinions of decision makers, and based on the characteristics of the vehicle scheduling platform, adherence to the principles of comprehensiveness, simplicity, scientificity, flexibility, and operability, as well as a combination of subjective and objective perspectives, regarding application and management are combined to determines C_1 (function and technology), C_2 (system strategy adaptability), C_3 (product supplier's ability) and C_4 (product after-sales service reputation) as the evaluation criteria for cloud service QoS. C_1 and C_2 reflect the application horizon, including the core content in the cloud service evaluation criteria designed and published by the ICSMA [49]. C_3 and C_4 reflect the management horizon. In order to select high-quality cloud services, an expert group consisting of eight direct managers (denoted as $E_1, E_2, \ldots, E_8$) was established. The alternative cloud service technologies A_1, A_2, A_3, and A_4 are given scores by the four suppliers. Figure 4 is a schematic of the evaluation criteria framework.

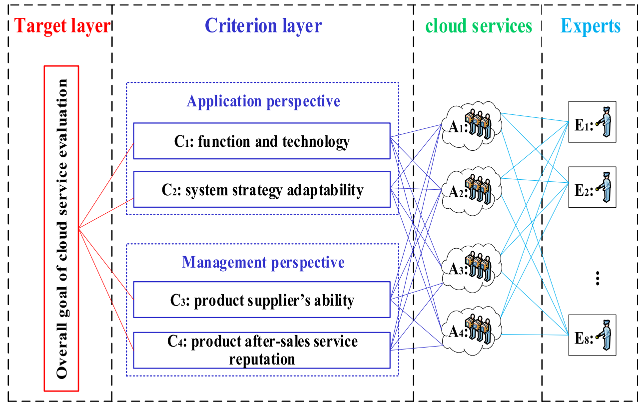

FIGURE 4. The framework of cloud service evaluation criteria.

TABLE 1. The expert's linguistic terms evaluation matrix.

A_i	E_1				E_2				…	E_8			
	C_1	C_2	C_3	C_4	C_1	C_2	C_3	C_4		C_1	C_2	C_3	C_4
A_1	S_5	S_2	S_4	S_4	S_4	S_3	S_3	S_6	…	S_4	S_3	S_1	S_5
A_2	S_5	S_5	S_6	S_3	S_4	S_4	S_5	S_4	…	S_5	S_5	S_5	S_4
A_3	S_2	S_5	S_3	S_2	S_1	S_5	S_2	S_3	…	S_1	S_5	S_2	S_3
A_4	S_5	S_6	S_0	S_3	S_4	S_5	S_1	S_2	…	S_4	S_5	S_1	S_2

Then, the eight decision makers are asked to assess each cloud service according to the above criteria using the linguistic assessment terms. The preset linguistic assessment terms set is {very poor, poor, medium poor, medium, medium good, good, very good} = $\{S_0, S_1, S_2, S_3, S_4, S_5, S_6\}$. The linguistic terms evaluation matrix provided by the expert group is presented in Table 1.

B. APPLICATION AND RESULTS

The application of the proposed scheme solves the problem of cloud service technology QoS evaluation, and the process is as follows.

Step 1 (Obtain the Cloud Model Decision Matrix): Using definition 6 and Equation (7), seven language scales can be converted into seven normal cloud model. Assuming $U = [0, 10]$, the seven clouds are: $y_0 = (0, 2.959, 0.125)$; $y_1 = (2.25, 2.655, 0.266)$; $y_2 = (3.85, 2.100, 0.411)$; $y_3 = (5.00, 1.922, 0.477)$; $y_4 = (6.15, 2.100, 0.411)$; $y_5 = (7.75, 2.655, 0.266)$; $y_6 = (10.00, 2.959, 0.125)$. According to the numerical characteristics of the seven normal clouds mentioned above, the linguistic terms can be transformed into the cloud model. Among them, the cloud model matrix from the first expert is shown in Table 2.

Step 2 (Calculate the Arithmetic Mean Cloud): Using Equation (8) to gather the cloud model decision matrix for all the cloud services as given by the eight experts, obtain the arithmetic mean cloud model $\overline{y}_{ij} = \left(\overline{Ex}_{ij}, \overline{En}_{ij}, \overline{H}e_{ij}\right)$ for the

TABLE 2. Cloud model decision matrix of the first decision-maker.

A_i	E_1			
	C_1	C_2	C_3	C_4
A_1	(7.75, 2.655, 0.266)	(3.85, 2.100, 0.411)	(6.15, 2.100, 0.411)	(6.15, 2.100, 0.411)
A_2	(6.25, 2.655, 0.266)	(7.75, 2.655, 0.266)	(10.00, 2.959, 0.125)	(5.00, 1.922, 0.477)
A_3	(3.85, 2.100, 0.411)	(7.75, 2.655, 0.266)	(5.00, 1.922, 0.477)	(3.85, 2.100, 0.411)
A_4	(7.75, 2.655, 0.266)	(10.00, 2.959, 0.125)	(0, 2.959, 0.125)	(5.00, 1.922, 0.477)

TABLE 3. The arithmetic mean cloud model matrix.

A_i	C_1	C_2	C_3	C_4
A_1	(6.981, 2.355, 0.256)	(4.021, 2.088, 0.416)	(6.080, 2.142, 0.416)	(6.231, 2.252, 0.403)
A_2	(6.653, 2.655, 0.266)	(7.631, 2.632, 0.223)	(9.847, 2.939, 0.139)	(5.288, 1.968, 0.461)
A_3	(3.527, 2.241, 0.385)	(7.536, 2.627, 0.296)	(4.792 1.981, 0.416)	(3.741, 2.142, 0.403)
A_4	(7.532, 2.621, 0.278)	(9.123, 2.959, 0.139)	(1.685, 2.959, 0.239)	(5.861, 2.056, 0.428)

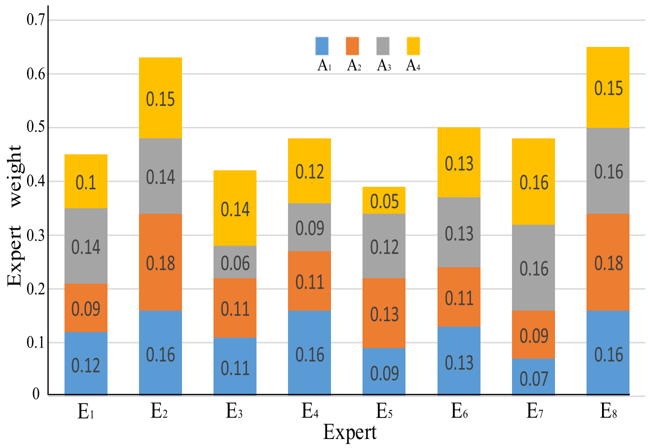

FIGURE 5. The dynamic expert weights for C1.

cloud service A_i QoS criteria C_j. The arithmetic mean cloud matrix $(\tilde{y}_{ij})_{4\times4}$ is shown in Table 3.

Step 3 (Determine the Dynamic Expert Weights): According to Equation (9), we calculate the similarity $\mathrm{sim}(y_{ij}^t, \bar{y}_{ij}^t)$ between the y_{ij}^t and $\bar{y}_{ij}^t$. Using Equation (10), we calculate the dynamic expert weights for different cloud services and different criteria. Figure 5 shows the dynamic expert weights in the alternative cloud service for C_1.

Step 4 (Obtain the Weighted Cloud Model Decision Matrix): Using Equation (11) to gather the cloud model decision matrix for the eight experts, obtain a weighted cloud model decision matrix composed of weighted clouds for different criteria for all cloud services, $\hat{Y}_k = (\hat{Y}_{ij})_{4\times4}$ shown in Table 4.

TABLE 4. Weighted cloud model decision matrix.

A_i	C_1	C_2	C_3	C_4
A_1	(6.671, 2.124, 0.228)	(4.125, 2.126, 0.398)	(6.219, 2.083, 0.398)	(6.223, 2.134, 0.412)
A_2	(6.589, 2.673, 0.283)	(7.128, 2.593, 0.218)	(9.135, 2.768, 0.146)	(5.103, 2.079, 0.471)
A_3	(3.146, 2.083, 0.376)	(7.023, 2.165, 0.301)	(5.129 2.013, 0.436)	(3.813, 2.098, 0.396)
A_4	(7.632, 2.753, 0.286)	(9.013, 3.125, 0.146)	(1.713, 3.015, 0.301)	(6.131, 2.236, 0.375)

TABLE 5. The positive-ideal solution and negative-ideal solution for the criteria.

	C_1	C_2	C_3	C_4
$\hat{y}_j^+$	(7.632, 2.753, 0.286)	(9.013, 3.125, 0.146)	(9.135, 2.768, 0.146)	(6.223, 2.134, 0.412)
$\hat{y}_j^+$	(3.146, 2.083, 0.376)	(4.125, 2.126, 0.398)	(1.713, 3.015, 0.301)	(3.813, 2.098, 0.396)

TABLE 6. The grey relationship coefficient of alternatives under each criterion.

A_i	r_{ij}^+				r_{ij}^-			
	C_1	C_2	C_3	C_4	C_1	C_2	C_3	C_4
A_1	0.455	0.318	0.423	0.813	0.887	0.452	0.281	0.660
A_2^-	0.432	0.412	0.813	0.465	0.570	0.917	0.690	0.434
A_3	0.387	0.403	0.346	0.328	0.728	0.897	0.917	0.430
A_4	0.912	0.446	0.415	0.639	0.304	0.554	0.380	0.592

Step 5 (Determine the Relative Closeness of Alternatives): Using Equation (12) to calculate the positive-ideal solution $\hat{y}_j^+$ and negative-ideal solution $\hat{y}_j^-$ in Table 4. Table 5 shows the calculation results.

We then calculate the grey relationship coefficient using Equations (14) and Equations (15). The results are shown in Table 6.

Let $w = (w_1, w_2, w_3, w_4)$ be the weight vector of criteria to be sought. Using Equation (18) to calculate the relative closeness of cloud services, the results are as follows.

$$\begin{aligned}
\partial_1 &= 0.399w_1 + 0.413w_2 + 0.601w_3 + 0.522w_4 \\
\partial_2 &= 0.431w_1 + 0.310w_2 + 0.541w_3 + 0.517w_4 \\
\partial_3 &= 0.347w_1 + 0.310w_2 + 0.274w_3 + 0.433w_4 \\
\partial_4 &= 0.750w_1 + 0.446w_2 + 0.522w_3 + 0.519w_4
\end{aligned}$$

Step 6 (Establish a Multi-Objective Optimization Model for Determining Optimal Criteria Weights): The set of criterion's weight information T given by the eight experts are

TABLE 7. The optimal weighted cloud decision matrix.

A_i	C_1	C_2	C_3	C_4
A_1	(2.148, 1.204, 0.129)	(0.912, 0.999, 0.187)	(2.015, 1.185, 0.226)	(0.828, 0.779, 0.150)
A_2	(1.834, 1.516, 0.160)	(1.575, 1.218, 0.102)	(2.960, 1.575, 0.083)	(0.679, 0.759, 0.172)
A_3	(1.013, 1.181, 0.213)	(1.552, 1.018, 0.141)	(1.662, 1.145, 0.248)	(0.507, 0.766, 0.145)
A_4	(2.458, 1.561, 0.219)	(1.992, 1.469, 0.069)	(0.555, 1.716, 0.171)	(0.815, 0.816, 0.137)

as follows:

$$T = \begin{cases} w_i > 0.10, i = 1, 2, 3, 4 \\ 0.08 < w_1 - w_2 < 0.12 \\ w_2 - w_4 > 0.05 \\ w_3 - w_1 < 0.02 \end{cases}$$

Therefore, establish the optimization model according to Equation (20).

$$\begin{aligned} &\text{Max } \partial_{(w)} \\ &\text{such that } \partial_1 = 0.399w_1 + 0.413w_2 + 0.601w_3 + 0.522w_4 \\ &\qquad \geq \partial_{(w)} \\ &\qquad \partial_2 = 0.431w_1 + 0.310w_2 + 0.541w_3 + 0.517w_4 \\ &\qquad \geq \partial_{(w)} \\ &\qquad \partial_3 = 0.347w_1 + 0.310w_2 + 0.274w_3 + 0.433w_4 \\ &\qquad \geq \partial_{(w)} \\ &\qquad \partial_4 = 0.750w_1 + 0.446w_2 + 0.522w_3 + 0.519w_4 \\ &\qquad \geq \partial_{(w)} \\ &\qquad 0.08 < w_1 - w_2 < 0.12 \\ &\qquad w_2 - w_4 > 0.05 \\ &\qquad w_3 - w_1 < 0.02 \\ &\qquad w_1 + w_2 + w_3 + w_4 = 1 \\ &\qquad w_i > 0.10, \quad i = 1, 2, 3, 4 \end{aligned}$$

Step 7 (Obtain the Optimal Criteria Weights): Determine the optimal weight of the QoS's criteria. By solving the above model, the optimal weights of the QoS indicators are: $w_1^* = 0.322$, $w_2^* = 0.221$, $w_3^* = 0.324$, $w_4^* = 0.133$.

Step 8 (Calculate the Optimally Weighted Cloud Decision Matrix): Using Equation (21) to determine the optimally weighted cloud decision matrix.

Step 9 (Determine the Positive-Ideal and the Negative-Ideal Solutions): The positive-ideal and negative-ideal solutions are calculated by Equation (22) and Equation (23), as shown in Table 8.

The results of the optimal weighted cloud model for each criterion of cloud services A_1, A_2, A_3 and A_4 are shown in Figure 6(a), Figure 6(b), Figure 6(c), and Figure 6(d). The corresponding positive-ideal and negative-ideal solution cloud model are shown in Figure 6(e) and Figure 6(f). The QoS of the corresponding cloud service can be seen intuitively by the point cloud distribution for each criterion.

TABLE 8. Positive-ideal and negative-ideal solution of the decision criteria.

	C_1	C_2	C_3	C_4
$\hat{z}_j^+$	(2.458, 1.561, 0.219)	(1.992, 1.469, 0.069)	(2.960, 1.575, 0.083)	(0.828, 0.779, 0.150)
$\hat{z}_j^-$	(1.013, 1.181, 0.213)	(0.912, 0.999, 0.187)	(0.555, 1.716, 0.171)	(0.507, 0.766, 0.145)

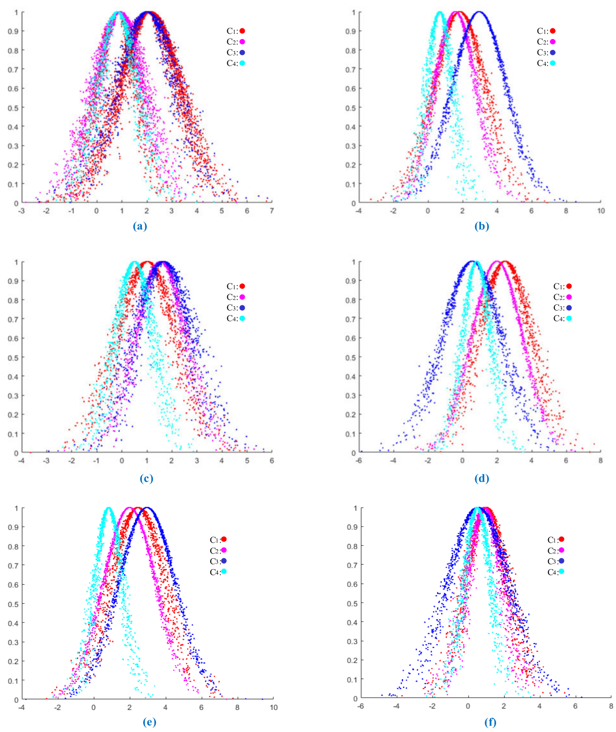

FIGURE 6. The optimal weighted cloud model for criteria.

TABLE 9. The distance between the alternatives and the ideal solution.

Distance	A_1	A_2	A_3	A_4
D_i^+	2.692	1.266	3.827	2.481
D_i^-	3.014	4.177	1.890	2.99

Step 10 (Calculate the Distance Between the Alternatives and the Ideal Solution): Equation (24) and Equation (25) are used to determine the distance between a cloud service's QoS and the ideal solution. The results are shown in Table 9.

Step 11 (Calculate the Relative Closeness of the Alternatives and Rank the Alternatives): We now calculate the relative closeness G_i of cloud service A_i, and the results are as follows: $G_1 = 0.528$, $G_2 = 0.767$, $G_3 = 0.331$, $G_4 = 0.547$. Therefore, the optimal ranking for the alternative cloud

TABLE 10. Ranking results of alternatives using different methods.

Alternatives	Fuzzy TOPSIS	Improved GRA	Improved VIKO R	The proposed method
A_1	2	3	3	3
A_2	1	1	1	1
A_3	4	4	4	4
A_4	3	2	2	2

services is $A_2 > A_4 > A_1 > A_3$, and the greatest QoS for enterprises is cloud service A_2.

C. COMPARATIVE STUDY

To verify the effectiveness and superiority of the evaluation method we propose, we performed an analysis based on the same case example and choose the fuzzy TOPSIS [53], the improved GRA [54], and the improved VIKOR [55] to facilitate comparative analysis. The ranking results of the four alternative cloud services determined by these methods are listed in Table 10.

From the results in Table 9, it is easy to see that the most suitable cloud service for the considered application is still A_2, according to both the proposed method and the listed methods. The cloud service ranking results of our proposed MCDM scheme are completely consistent with the ranking results obtained through the improved VIKOR method and the improved GRA method. That proves the effectiveness of the proposed method. However, compared with the listed methods, the apparent advantages of the method proposed in this study are as follows:

(1) Using the cloud model theory, the model can reflect both the vagueness of linguistic evaluation information and the randomness of criteria. Our method preserves the integrity of linguistic information to achieve conversion of qualitative information into quantitative information.

(2) The proposed method considers that decision makers adopt psychological behaviors such as reference dependence and loss aversion. Using the cloud distance measurement algorithm to calculate the distance and similarity between each expert evaluation cloud and the arithmetic average cloud to determine the dynamic experts weights can avoid the subjective negative influence of the decision maker.

(3) TOPSIS improved by the GRA is used to define the relative closeness of alternatives. By establishing a multi-objective optimization model that maximizes the relative closeness of all alternatives, the optimal criteria weights can be determined more accurately, objectively and reasonably.

D. SENSITIVITY ANALYSIS

Taking into account that because experts will always lack knowledge to a certain extent, and that knowledge itself has limitations, there is an inherent uncertainty in the evaluation of some program criteria; therefore, we use the perturbation method to conduct a sensitivity analysis of expert evaluation, that is, after the expert evaluation in decision-making is slightly disturbed, each potential cloud corresponds to changes in service priorities. Disturbance expert E_k evaluates S_n on the linguistic term of criterion C_j, and records the disturbance as S_m, and m is not equal to n. E_3 and E_7 are randomly selected, and the evaluations of these two experts on different criteria are disturbed, respectively. m takes all the numbers from 0 to 6 except n in turn, for 48 trials. We then calculate the final relative closeness of different cloud services, and produce the result shown in Figure 7.

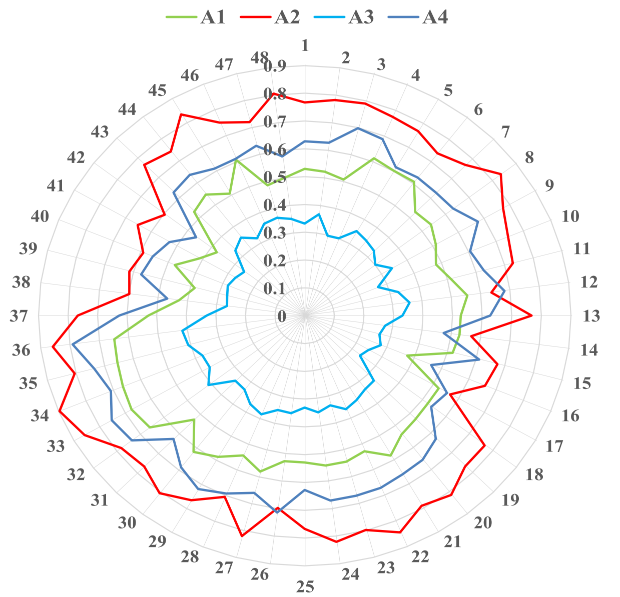

FIGURE 7. Sensitivity analysis of our proposed MCDM scheme.

It can be seen from Figure 7 that the evaluation changes made by the experts on the criteria have a significant impact on the relative closeness of the alternatives because the multi-criteria decision-making framework we propose uses the same group of experts to evaluate the weights and indicators, and the individual experts' determinations will have a more significant impact on the results. However, the stability of the optimal scheme obtained in the 48 test results is relatively good (the optimal scheme has only changed 2 times, accounting for 4.2% of the total test). In the actual evaluation, the expert group can participate in evaluating the criteria and analyzing the impact of the relationship between the criteria at the same time, which is more suitable for management and decision-making regarding cloud service choice for the vehicle dispatching platform. The proposed method heightens the already dominant position of cloud service purchasers in cloud service management and supervision.

V. CONCLUSION AND FUTURE WORK

In this study, we present a practical integrated MCDM scheme for cloud systems that assesses and selects the most appropriate cloud service considering QoS criteria. From the perspective of cloud drop distribution, we propose a more comprehensive and accurate cloud model distance measurement algorithm, and apply it to the calculation of cloud model similarity and the gray correlation coefficient. The dynamic expert weights are determined by calculating the similarity between the expert evaluation cloud model and the arithmetic mean cloud model. By establishing a multi-objective optimization model, the proposed method maximizes the relative closeness of all alternatives to determine the weights of the criteria. In addition, we propose an improved TOPSIS based on GRA, using the cloud mode's grey relational coefficient to replace the direct weighted average method in the classic TOPSIS method to analyze the similarities and differences between the alternatives, and calculate the relative closeness between the alternatives and the ideal solution. The cloud model is used to represent decision-makers linguistic evaluation of alternative cloud services and an extension of the classical TOPSIS is applied to generate alternative rankings.

Finally, as an illustrative example of introducing cloud services into the scheduling platform of a mining company, we reconstructed the QoS evaluation criteria for cloud services from both application and service perspectives and verified the effectiveness and robustness of the proposed MCDM scheme. It is shown that the proposed cloud distance measurement algorithm, from the perspective of cloud droplet distribution, can effectively reflect the differences between cloud models from a global perspective. Improved TOPSIS based on GRA can ensure the consistency of the score differences between the evaluation criteria when solving for the criterion weights. Altogether, the proposed MCDM solution can provide customers with decision-making consultations as the demand for cloud services increases and can also provide guidance for the development direction of cloud service providers.

Even with the advantages of our proposed scheme, there are some limitations and room for further research. First, the proposed method assumes that the deterministic linguistic measurement provided by decision makers regarding the alternative cloud services are correct. However, due to the cognitive limitations of decision-makers, the evaluation of indicators in the real world is often vague. Therefore, in the future, we can use vague language terms to evaluate indicators and study how to quantify them as cloud models. Second, in the future, by studying the actual application of cloud service in enterprises, building a more refined evaluation index system and obtaining accurate evaluation index data, re-evaluating the QoS of cloud services, and verifying the effectiveness of the proposed methods, we can improve cloud service QoS evaluation. Third, the proposed method's calculation time can be significantly reduced through software development techniques that will facilitate a faster the evaluation and selection of the cloud service with the highest QoS. Additionally, the proposed method should further expand cloud service selection research by analyzing other cloud services to enhance the external validity and universal applicability of the research results.

APPENDIX
QUESTIONNAIRE ON QoS OF CLOUD SERVICES

The company needs to purchase cloud services for the truck dispatch platform. Currently, four cloud service suppliers provide four cloud services A_1, A_2, A_3 and A_4 as alternatives. The content of the cloud service evaluation criteria is described in the questionnaire. Please evaluate the alternatives according to the cloud service information provided by the suppliers and carefully compare the content of the cloud service evaluation criteria. The preset linguistic assessment terms set is {very poor, poor, medium poor, medium, medium good, good, very good} $= \{S_0, S_1, S_2, S_3, S_4, S_5, S_6\}$. Please fill in the "Level" column.

Your evaluation is very important to the company's development, and please be sure to fill it out carefully.

Thanks for your cooperation!

Alternatives	Criteria	Level
A_1	C_1: function and technology	
	C_2: system strategy adaptability	
	C_3: product supplier's ability	
	C_4: product after-sales service reputation	
A_2	C_1: function and technology	
	C_2: system strategy adaptability	
	C_3: product supplier's ability	
	C_4: product after-sales service reputation	
A_3	C_1: function and technology	
	C_2: system strategy adaptability	
	C_3: product supplier's ability	
	C_4: product after-sales service reputation	
A_4	C_1: function and technology	
	C_2: system strategy adaptability	
	C_3: product supplier's ability	
	C_4: product after-sales service reputation	
Description of evaluation criteria for QoS of cloud service		
C_1	Timeliness, accuracy, reliability, cost performance, robustness, and security of cloud service	
C_2	The level of collaboration, integration, intelligence, maintainability, availability, and flexibility of cloud service	
C_3	Operation, organization and management, R&D, innovation, and profitability of cloud service supplier	
C_4	Operation and maintenance costs, service attitudes and reputation of cloud services	

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