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Research Article

A Heterogeneous QoS-Based Cloud Service Selection Approach Using Entropy Weight and GRA-ELECTRE III

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With the development of cloud computing, more and more resources are provided in the form of cloud services. Then how to select suitable cloud service for users without professional knowledge has become an important issue. Existing cloud service selection models are usually considered as QoS-aware evaluation focused models. In practice, the QoS attributes have problems like subjectivity, vagueness, and uncertainty, and a range of formats are involved to describe QoS attributes. Therefore, it is necessary to consider the heterogeneous formats of QoS attributes in cloud service selection process. The aim of this paper is to develop a novel cloud service selection approach using entropy weight and GRA-ELECTRE III that can handle heterogeneous QoS attributes simultaneously. In the proposed approach, heterogeneous QoS attributes are handled simultaneously by being transformed into intuitionistic fuzzy numbers; the relative weights of QoS attributes are calculated objectively by the extended entropy measure method under intuitionistic fuzzy environment; and cloud services are evaluated by GRA-ELECTRE III integrated method under intuitionistic fuzzy environment. Experimental results show that the proposed approach has good stability and discrimination in dealing with heterogeneous data and can effectively avoid compensation between attributes.

1. Introduction

Cloud computing is a model for realizing ubiquitous, on-demand network access to shared pools of configurable computing resources such as networks, servers, storage, applications, and services [1]. The rise and development of cloud computing has led to the emergence of a large number of cloud services [2]. When decision makers select cloud service from a set of available services with equivalent functions, the nonfunctional performance of cloud service described by quality of service (QoS) attributes determine final choice. In the market, multiple functionally equivalent cloud services with different QoS attributes are often available for specific domains [3]. However, users lack sufficient information and appropriate benchmarks to evaluate cloud services according to individual preferences. Therefore, cloud service selection problem becomes a big challenge and attracts a huge amount of attention from both academia and industry.

A range of advanced techniques have been developed to assist users to choose suitable services [4–6]. Most of the existing cloud service selection models are considered as QoS-aware evaluation focused models. In practice, the QoS attributes have problems like subjectivity, vagueness, and uncertainty [7]. For instance, the access reliability of cloud service is strongly affected by decision maker's subjective perception, and corresponding rating on this attribute is vague. Subsequently, a range of formats are involved to describe the QoS attributes, such as crisp data, interval data, triangular fuzzy number (TFN), and intuitionistic fuzzy number (IFN), etc. Although researchers have tried to solve these problems [7–9], existing models cannot handle these heterogeneous QoS attributes simultaneously. In this research, the heterogeneous QoS data are transformed into IFNs; then the heterogeneous QoS attributes can be handled simultaneously.

Sometimes the values of different QoS attributes cannot compensate for each other completely. For instance, the low cost of cloud service should compensate for its low reliability; otherwise, the huge cost superiority masks the defect of low reliability. Therefore, noncompensatory methods are more suitable to evaluate cloud service. The Elimination and Choice Translating Reality (ELECTRE) originally proposed by Roy [10] is a typical representative of noncompensatory multicriteria decision-making (MCDM) methods; alternatives are compared on each criterion and scores on criteria cannot completely compensate for each other. The ELECTRE III is an improvement of ELECTRE I, which can deal with inaccurate, loose, vague, or ill-determined data [11]. Therefore, ELECTRE III is adopted to evaluate alternative cloud services in this research. Grey relation analysis (GRA) proposed by Deng [12] is an impact evaluation method that can measure the relation between the reference series and comparison series. In this research, GRA is used to modify the ELECTRE III method under intuitionistic fuzzy environment to better reflect the relationship between QoS attributes.

The aim of this paper is to develop a novel cloud service selection approach using entropy weight and GRA-ELECTRE III under intuitionistic fuzzy environment. The contributions of this research are illustrated as follows.

Firstly, a novel cloud service selection method is proposed to handle heterogeneous QoS attributes simultaneously. In this research, heterogeneous QoS data are transformed into IFNs; then the vagueness and uncertainty are better preserved.

Secondly, the entropy measure method is extended under intuitionistic fuzzy environment to determine the weights of QoS attributes. This weight determination method can avoid decision maker's subjective judgments.

Finally, the GRA-ELECTRE III-integrated method is proposed to evaluate cloud services under intuitionistic fuzzy environment. This method can effectively avoid mutual compensation between QoS attributes and reflect the weak preferences and indifference among alternatives.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 proposes preliminaries of triangular fuzzy set (TFS), Intuitionistic fuzzy set (IFS), interval number, entropy measure, and ELECTRE III. Section 4 proposes the cloud service selection approach considering the heterogeneity of QoS attributes. Experiments are conducted in Section 5 to demonstrate the application and efficiency of the proposed cloud service selection approach. Finally, conclusions and future work follow in Section 6.

2. Literature Review

The QoS-aware cloud service selection problem can be considered as a MCDM problem [13]. Multiple methods has been proposed by researchers to evaluate cloud services [4, 6, 14]. Existing MCDM methods can be divided into two parts: weight determination and alternative evaluation. Researchers proposed different methods for weight determination, such as Delphi, Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), entropy measure, etc. [15–17]. The entropy concept first introduced by Shannon and Weaver [18] is a measure that uses probability theory to measure the uncertainty of information. Since the entropy measure method is objective and can make full use of the original data, the entropy measure method is adopted to calculate the weights of QoS attributes.

The evaluation methods can be classified into compensatory decision rules and noncompensatory decision rules [19]. Compensatory decision rules assume that a bad performance of an alternative on a particular criterion can be compensated by high scores on other criteria, such as AHP, ANP, Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), Multicriteria Optimization and Compromise Solution (VIKOR), etc. Conversely, noncompensatory decision rules assume that a bad performance of an alternate on a particular criterion cannot be compensated by high scores on other criteria, such as ELECTRE and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [20]. Since the values of QoS attributes cannot compensate for each other completely, noncompensatory algorithms are more suitable to evaluate cloud service.

ELECTRE first proposed by Roy [10] is a popular outranking method. Its principle is to deal with a pair of decisions in order to obtain a binary relation about the decision set and it is a typical representative of noncompensatory algorithm. The advantage of ELECTRE is to process incomplete information by considering the indifference threshold and preference threshold [21]. Several other ELECTRE methods were developed during the following two decades: ELECTRE II [22], ELECTRE III [23], ELECTRE IV [24], ELECTRE, and TRI [25]. Obviously, each of the ELECTRE versions differs operationally. The ELECTRE II, ELECTRE III, and ELECTRE IV were designed to rank alternatives while the ELECTRE TRI was proposed to solve assignment problems. Regarding the ranking methods, the ELECTRE II establishes the concordance, discordance, and indifference sets to capture the outranking relations between alternatives; the ELECTRE III method takes into account the ambiguous and uncertain information [26]. ELECTRE II uses real standards, while III and IV use pseudo standards. ELECTRE III uses weights to make decisions, while ELECTRE IV does not. ELECTRE TRI is suitable for assigning alternatives to a predefined set of categories [27]. Therefore, due to the noncompensatory nature of ELECTRE III, the characteristics that apply to the sorting problem and can take weights into account, ELECTRE III is adopted for cloud service selection. GRA proposed by Deng [12] is a popular MCDM method that can measure the similarity or difference between two series according to the relationship between them. When the relationship between complex factors in the system can be tested by distance measurement, both qualitative and quantitative relationships can be identified by GRA [28]. Therefore, GRA is used to modify the ELECTRE III method.

In order to deal with fuzzy and uncertain information, many extended methods have been proposed to solve MCDM problems under uncertain environment. For example, fuzzy DEMATEL, fuzzy TOPSIS, fuzzy VIKOR, fuzzy ELECTRE, fuzzy PROMETHEE, or fuzzy hybrid methods

[29–32]. Meanwhile, Joshi and Kumar [33] proposed a new fuzzy divergence measure and its application in TOPSIS. Joshi [34] introduced a new biparametric exponential information measure based on IFSs. Joshi and Kumar [35] extended a two-parametric intuitionistic fuzzy information measure to VIKOR. Joshi and Kumar [36] proposed a new multiple attribute decision-making method based on weighted correlation coefficients under intuitionistic fuzzy environment. These methods provide a lot of references for the extension of the MCDM method, but they are based on a single fuzzy environment without taking the heterogeneous environment into account.

Some models took incomplete preference information and incomplete weight information into account in heterogeneous environment, and extended hesitation degrees [37–39], Atanassov's intuitionistic fuzzy truth degrees [40], and interval-valued intuitionistic fuzzy truth degrees [41] to linear programming technique for multidimensional analysis of preference method to deal with heterogeneous MCDM problem. To transform heterogeneous data into a unified format, Xu et al. [39] put forward a method of transforming heterogeneous data into IFNs. Wan et al. [42] transformed heterogeneous data into interval IFNs. Xu et al. [43] transformed heterogeneous data into intuitionistic TFNs. Due to the wide application of IFNs, this paper transforms heterogeneous data into IFNs. In this research, the entropy measure method and ELECTRE III will be extended to intuitionistic fuzzy environment.

3. Preliminaries

This section briefly describes the TFS, IFS, entropy measure method, and ELECTRE III method.

3.1. Triangular Fuzzy Set (TFS)

Definition 1 (see [44]). A TFN $\widetilde{A}$ is defined as (a_1, a_2, a_3), where a_1 is the minimum possible value, a_2 is the most possible value, and a_3 is the maximum possible value. When $a_1 = a_2 = a_3$, $\widetilde{A}$ is the crisp value. The membership function $\mu_{\widetilde{A}}(x)$ is defined as

$$\mu_{\widetilde{A}}(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1}, & a_1 \leq x \leq a_2, \\ \\ \dfrac{a_3 - x}{a_3 - a_2}, & a_2 \leq x \leq a_3, \\ \\ 0, & \text{otherwise}. \end{cases} \quad (1)$$

Definition 2 (see [44]). Let $\widetilde{A} = (a_1, a_2, a_3)$ and $\widetilde{A}' = (a_1', a_2', a_3')$ be two TFNs, the distance between them is calculated by

$$d\left(\widetilde{A}, \widetilde{A}'\right) = \sqrt{\frac{1}{3}\left[\left(a_1 - a_1'\right)^2 + \left(a_2 - a_2'\right)^2 + \left(a_3 - a_3'\right)^2\right]}. \quad (2)$$

3.2. Intuitionistic Fuzzy Set (IFS)

Definition 3 (see [45]). Let X be a finite nonempty set. A IFS A can be described as

$$A = \{ < x, \mu_A(x), \nu_A(x) > | \, x \in X \}, \quad (3)$$

where $\mu_A(x)$ and $\nu_A(x)$ denote the membership degree and nonmembership degree of element x to the IFS A, $\mu_A(x)$, $\nu_A(x) \in [0, 1]$, and $0 \leq \mu_A(x) + \nu_A(x) \leq 1$.

Degree of hesitation $\pi_A(x)$ of the element x to A is defined as $\pi_A(x) = 1 - (\mu_A(x) + \nu_A(x))$. $\pi_A(x) \in [0, 1]$, if $\pi_A(x) = 0$, the IFS A is similar to a fuzzy set.

Definition 4 (see [46]). Let $A = (\mu_A, \nu_A, \pi_A)$ and $B = (\mu_B, \nu_B, \pi_B)$ be two IFNs, the distance between them is

$$d(A, B) = \sqrt{\frac{1}{2}\left[\left(\mu_A - \mu_B\right)^2 + \left(\nu_A - \nu_B\right)^2 + \left(\pi_A - \pi_B\right)^2\right]}. \quad (4)$$

Definition 5 (see [47]). Let $A_1 = (\mu_{A_1}, \nu_{A_1})$ and $A_2 = (\mu_{A_2}, \nu_{A_2})$ be two IFNs, then the follow rules are obtained.

$$\begin{aligned} \mathrm{A}_1 \oplus \mathrm{A}_2 &= \left(\mu_{\mathrm{A}_1} + \mu_{\mathrm{A}_2} - \mu_{\mathrm{A}_1}\mu_{\mathrm{A}_2},\ \nu_{\mathrm{A}_1}\nu_{\mathrm{A}_2}\right), \\ \lambda A_1 &= \left(1 - \left(1 - \mu_{A_1}\right)^{\lambda}, \nu_{A_1}^{\lambda}\right). \end{aligned} \quad (5)$$

Definition 6 (see[47]). Let $A_j = (\mu_{A_j}, \nu_{A_j}) \, (j = 1, 2, \ldots\ldots, n)$ be a collection of IFNs, ω_j $(\sum_{j=1}^{n} \omega_j = 1)$ is the weight vector. The generalized intuitionistic fuzzy weighted averaging (GIFWA) operator is as follows:

$$\text{GIFWA} = \left\{ \left(1 - \prod_{j=1}^{n} \left(1 - \mu_{A_j}\right)^{\omega_j}\right), \prod_{j=1}^{n} \nu_{A_j}^{\omega_j} \right\}. \quad (6)$$

3.3. Interval Number

Definition 7 (see [45]). Let $A = [a_1, a_2]$ and $B = [b_1, b_2]$ be two interval numbers, and the distance between them is

$$d(A, B) = \frac{1}{2}\left(\left|a_1 - b_1\right| + \left|a_2 - b_2\right|\right). \quad (7)$$

3.4. Entropy Measure. The entropy concept first introduced by Shannon and Weaver [18] shows that the more dispersive the data, the bigger the uncertainty, and the more important the criterion. The decision information of each criterion can be expressed by entropy value, and then the relative importance of the criterion can be determined objectively. Suppose that a MCDM problem has m alternatives $A = \{A_1, A_2, \ldots, A_m\}$, and n decision criteria $C = \{C_1, C_2, \ldots, C_n\}$. Each alternative evaluated with respect to the n criteria form a decision matrix denoted by $G = (g_{ij})_{m \times n}$. Then the entropy weight can be summarized as following steps:

Step 1: calculate the entropy measure of each criterion e_j by the following equation:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij}\cdot \ln p_{ij}, p_{ij} = \frac{g_{ij}}{\sum_{i=1}^{m} g_{ij}}, 0\ln 0 \equiv 0, i = 1,2,\ldots,m, j = 1,2,\ldots,n. \tag{8}$$

Step 2: define the divergence d_j through the following equation, the more the divergence is, the more important the criterion is

$$d_j = 1 - e_j, \quad j = 1,2,\ldots,n. \tag{9}$$

Step 3: calculate the normalized criteria weights w_j by the following equation:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}, \quad j = 1,2,\ldots,n. \tag{10}$$

3.5. ELECTRE III. ELECTRE III well reflects the indifference and weak preference of evaluation. ELECTRE III performs well in dealing with inaccurate, uncertain data by defining three thresholds: indifference (q), preference (p), and veto (v). $q_j\,(j = 1,2,\ldots,n)$ is the indifference threshold between $A_i\,(i = 1,2,\ldots,m)$ and $A_k\,(k = 1,2,\ldots,m)$ on $C_j\,(j = 1,2,\ldots,n)$, when the difference between A_i and A_k on C_j is less than q_j, there is no difference between A_i and A_k on C_j. $p_j\,(j = 1,2,\ldots,n)$ is the preference threshold between A_i and A_k on C_j, when the difference between A_i and A_k on C_j is larger than p_j, it is considered that A_i is strictly superior to A_k. $v_j\,(j = 1,2,\ldots,n)$ is the veto threshold between A_i and A_k on C_j, when the evaluation value of A_i is lower than A_k on C_j and the difference is equal or greater than v_j, it is no longer recognized that A_i is superior to A_k in general. Suppose a and b are two alternatives, ELECTRE III has following definition [48]:

$$\begin{cases} g(a) > g(b) + p(g(b)) \Longleftrightarrow aPb\ (a \text{ is strictly preferred to } b), \\ g(b) + q(g(b)) < g(a) < g(b) + p(g(b)) \Longleftrightarrow aQb\ (a \text{ is weekly preferred to } b), \\ g(b) < g(a) < g(b) + q(g(b)) \Longleftrightarrow aIb\ (a \text{ is indifferent to } b). \end{cases} \tag{11}$$

The traditional ELECTRE III method is illustrated as follows [49].

Step 1: Determine the value of q_j, p_j, and v_j.

$$q_j = \alpha\left(\max g_j - \min g_j\right)(j = 1,2,\ldots,n), \tag{12}$$

where α is the certain multiple and $0.05 \le \alpha \le 0.1$, $\max g_j$ is the largest evaluation value of C_j and $\min g_j$ is the smallest evaluation value of C_j.

$$p_j = \beta q_j\,(j = 1,2,\ldots,n). \tag{13}$$

where β is the certain multiple and $3 \le \beta \le 10$.

$$v_j = \gamma\left(\max g_j - \min g_j\right)(j = 1,2,\ldots,n). \tag{14}$$

where γ is the certain multiple and $0.5 \le \gamma \le 1$.

Step 2: Calculate concordance index $C(a,b)$. Concordance index $C(a,b)$ measures the support strength that a is at least as good as b.

$$c_j(a,b) = \begin{cases} 0, & \text{if } g_j(b) \ge g_j(a) + p_j\left(g_j(a)\right) \\ 1, & \text{if } g_j(b) \le g_j(a) + q_j\left(g_j(a)\right) \\ \dfrac{g_j(a) + p_j\left(g_j(a)\right) - g_j(b)}{p_j\left(g_j(a)\right) - q_j\left(g_j(a)\right)}, & \text{otherwise} \end{cases} \left(j = 1,2,\ldots,n\right),$$

$$C(a,b) = \frac{\sum_{j=1}^{n} w_j\cdot c_j(a,b)}{\sum_{j=1}^{n} w_j} \quad (j = 1,2,\ldots,n). \tag{15}$$

Step 3: Calculate the credibility score $S(a,b)$. Credibility score $S(a,b)$ measures the credibility degree that a at least as good as b.

$$S(a,b)=\begin{cases} C(a,b), & \text{if } D_j(a,b)\le C(a,b) \\ C(a,b)\cdot \prod_{D_j(a,b)>C(a,b)} \dfrac{1-D_j(a,b)}{1-C(a,b)}, & \text{otherwise} \end{cases} \quad (j=1,2,\ldots,n). \tag{16}$$

where the $D_j(a,b)$ is the discordance index, it measures the strength of the evidence against that a at least as good as b.

$$D_j(a,b)=\begin{cases} 0, & \text{if } g_j(b)\le g_j(a)+p_j\big(g_j(a)\big) \\ 1, & \text{if } g_j(b)\ge g_j(a)+v_j\big(g_j(a)\big) \\ \dfrac{g_j(b)-p_j\big(g_j(a)\big)-g_j(a)}{v_j\big(g_j(a)\big)-p_j\big(g_j(a)\big)}, & \text{otherwise} \end{cases} \quad (j=1,2,\ldots,n). \tag{17}$$

Step 4: Distillation procedure:

Step 4.1: Determine the cut off level of outranking.

$$\lambda_1=\max_{\{S(a,b)<\lambda_0-s(\lambda_0)\}} S(a,b). \tag{18}$$

where $\lambda_0=\max S(a,b)$ and $s(\lambda_0)$ is the discrimination threshold at the maximum level of outranking λ_0.

$$s(\lambda)=0.3-0.15\lambda. \tag{19}$$

a outranks b if $S(a,b)>\lambda_1$ and $S(a,b)-S(b,a)>s(\lambda)$.

Step 4.2: If a outranks b, a is recorded as +1 and b is recorded as −1. Add the scores for every alternative to get the final score.

Step 4.3: Descending distillation: the alternative with the highest final score is placed in the sort and the remaining alternatives are repeated for the above steps.

Step 4.4: Ascending distillation: the alternative with the lowest final score is placed in the sort and the remaining alternatives are repeated for the above steps.

Step 5: Combine the results of the two distillation procedures to get the final sort.

4. The Proposed Cloud Service Selection Approach

4.1. QoS Attributes. As shown in Table 1, the five most frequently used QoS attributes *cost*, *response time*, *availability*, *reliability*, and *reputation* are used in this research [50, 51]. *Cost* and *response time* are cost criteria, the smaller the better. *Availability*, *reliability*, and *reputation* are benefit criteria, the larger the better. *Cost* is crisp data provided by the cloud service provider. *Response time* is an interval depending on the environment such as the network; therefore, it is represented by the interval data. *Availability* is crisp data retrieved directly from the records of the cloud service platform. *Reliability* varies based on a specific value in different transmission environment, so TFNs are more suitable to represent it. *Reputation* is evaluated by the user after the service is finished, it is often difficult for users to describe with crisp data. Therefore, QoS attributes are represented by multiple formats, such as crisp data, interval data, TFN and IFN. In most cases, linguistic variables are used for evaluation, but it will relatively restrict the expression of users. Therefore, the IFNs reflect the user's satisfaction and dissatisfaction through membership and nonmembership more intuitively.

Since heterogeneous data formats are involved in this research to represent QoS attributes, all these data formats

Table 1: QoS attributes and illustrations.

ID	QoS attributes	Illustrations	Formats
C1	Cost	The service fee that the user needs to pay the service provider	Crisp data
C2	Response time	Time interval from the request is made to the response is received	Interval data
C3	Availability	It is the probability that a user service can be accessed	Crisp data
C4	Reliability	The ability to run according to performance requirements	Triangular fuzzy number
C5	Reputation	It is a measure of the credibility of a service, usually from user feedback	Intuitionistic fuzzy number

can be converted into IFNs by the method proposed by Xu et al. [39]. Suppose that a MCDM problem has m alternatives $A=\{A_1,A_2,\ldots,A_m\}$, and n decision criteria $C=\{C_1,C_2,\ldots,C_n\}$. Each alternative evaluated with respect to the n criteria forms a benefit decision matrix denoted by $X\prime=(x'_{ij})_{m\times n}$. $d(a,b)$ is the distance between a and b. In this case, all values are given by the cloud service platform, which can be regarded as a single expert decision. Then conversion process is illustrated as following.

Step 1: Suppose that C_j is benefit criteria. Calculate Quasi-satisfactory value (ξ), Quasi-dissatisfactory value (ζ), and Quasi-uncertain value (η) of x'_{ij}.

$$\xi_{ij}=\left\{x'_{ij}, d\left(x'_{ij},C_j^{\max}\right)<d\left(x'_{ij},C_j^{\min}\right)C_j^{\mathrm{mid}},\quad \text{other}\quad (i=1,2,\ldots,m,\quad j=1,2,\ldots,n),\right. \tag{20}$$

$$\zeta_{ij}=\left\{x'_{ij}, d\left(x'_{ij},C_j^{\max}\right)>d\left(x'_{ij},C_j^{\min}\right)C_j^{\mathrm{mid}},\quad \text{other}\quad (i=1,2,\ldots,m,\quad j=1,2,\ldots,n),\right. \tag{21}$$

$$\eta_{ij}=\frac{\xi_{ij}+\zeta_{ij}}{2}\quad (i=1,2,\ldots,m,\quad j=1,2,\ldots,n), \tag{22}$$

where $C_j^{\mathrm{mid}}=(C_j^{\max}+C_j^{\min})/2$, $C_j^{\max}$, and $C_j^{\min}$ are the largest and smallest value of C_j. In order to retain more evaluation information, $C_j^{\max}$ and $C_j^{\min}$ are defined as follows:

$$C_j^{\max}=\begin{cases} x_j^+, & \text{criteria } j \text{ is crisp data,}\\ \left[b_{1j}^+,b_{2j}^+\right], & \text{criteria } j \text{ is interval data,}\\ \left(a_{1j}^+,a_{2j}^+,a_{3j}^+\right), & \text{criteria } j \text{ is triangular fuzzy number,}\\ \left(\mu_j^+,\nu_j^+\right), & \text{criteria } j \text{ is intuitionistic fuzzy number,}\end{cases} \tag{23}$$

$$C_j^{\min}=\begin{cases} x_j^-, & \text{criteria } j \text{ is crisp data,}\\ \left[b_{1j}^-,b_{2j}^-\right], & \text{criteria } j \text{ is interval data,}\\ \left(a_{1j}^-,a_{2j}^-,a_{3j}^-\right), & \text{criteria } j \text{ is triangular fuzzy number,}\\ \left(\mu_j^-,\nu_j^-\right), & \text{criteria } j \text{ is intuitionistic fuzzy number,}\end{cases} \tag{24}$$

where $x_j^+=\max\{x'_{ij}\,|\,i=1,\ldots\ldots,m\}$, $b_{1j}^+=\max\{b_{1ij}\,|\,i=1,\ldots\ldots,m\}$, $b_{2j}^+=\max\{b_{2ij}\,|\,i=1,\ldots\ldots,m\}$, $a_{1j}^+=\max\{a_{1ij}\,|\,i=1,\ldots\ldots,m\}$, $a_{2j}^+=\max\{a_{2ij}\,|\,i=1,\ldots\ldots,m\}$, $a_{3j}^+=\max\{b_{3ij}\,|\,i=1,\ldots\ldots,m\}$, $\mu_j^+=\max\{\mu_{ij}\,|\,i=1,\ldots\ldots,m\}$, $\nu_j^+=\min\{\nu_{ij}\,|\,i=1,\ldots\ldots,m\}$, $x_j^-=\min\{x'_{ij}\,|\,i=1,\ldots\ldots,m\}$, $b_{1j}^-=\min\{b_{1ij}\,|\,i=1,\ldots\ldots,m\}$, $b_{2j}^-=\min\{b_{2ij}\,|\,i=1,\ldots\ldots,m\}$, $a_{1j}^-=\min\{a_{1ij}\,|\,i=1,\ldots\ldots,m\}$, $a_{2j}^-=\min\{a_{2ij}\,|\,i=1,\ldots\ldots,m\}$, $a_{3j}^-=\min\{b_{3ij}\,|\,i=1,\ldots\ldots,m\}$, $\mu_j^-=\min\{\mu_{ij}\,|\,i=1,\ldots\ldots,m\}$, $\nu_j^-=\max\{\nu_{ij}\,|\,i=1,\ldots\ldots,m\}$ [52]. The cardinalities of the uncertain set are always equal to 1 in this paper.

Step 2: Calculate the Quasi-membership degree (κ), Quasi-nonmembership degree (ς), and Quasi-hesitancy degree (τ).

$$\kappa_{ij} = \frac{d\left(\xi_{ij}, C_j^{\text{mid}}\right)}{d\left(\xi_{ij}, C_j^{\text{mid}}\right) + d\left(\xi_{ij}, C_j^{\text{max}}\right)} \quad (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n), \tag{25}$$

$$\varsigma_{ij} = \frac{d\left(\zeta_{ij}, C_j^{\text{mid}}\right)}{d\left(\zeta_{ij}, C_j^{\text{mid}}\right) + d\left(\zeta_{ij}, C_j^{\text{min}}\right)} \quad (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n), \tag{26}$$

$$\tau_{ij} = \begin{cases} \dfrac{d\left(\zeta_{ij}, \eta_{ij}\right)}{d\left(\zeta_{ij}, \eta_{ij}\right) + d\left(\eta_{ij}, C_j^{\text{mid}}\right)}, d\left(\eta_{ij}, C_j^{\text{max}}\right) > d\left(\eta_{ij}, C_j^{\text{min}}\right) \\ \dfrac{d\left(\xi_{ij}, \eta_{ij}\right)}{d\left(\xi_{ij}, \eta_{ij}\right) + d\left(\eta_{ij}, C_j^{\text{mid}}\right)}, d\left(\eta_{ij}, C_j^{\text{max}}\right) < d\left(\eta_{ij}, C_j^{\text{min}}\right) \\ 1, d\left(\eta_{ij}, C_j^{\text{max}}\right) = d\left(\eta_{ij}, C_j^{\text{min}}\right) \end{cases} \quad (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n), \tag{27}$$

Step 3: In an IFN, the membership degree (μ_{ij}), nonmembership degree (ν_{ij}), and hesitancy degree (π_{ij}) are defined as follows:

$$\mu_{ij} = \begin{cases} \dfrac{\kappa_{ij}}{\kappa_{ij} + 1/2\tau_{ij}}, & d\left(x_{ij}, C_j^{\text{max}}\right) < d\left(x_{ij}, C_j^{\text{min}}\right) \\ 0, & \text{other} \end{cases} \quad (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n), \tag{28}$$

$$\nu_{ij} = \begin{cases} \dfrac{\varsigma_{ij}}{\varsigma_{ij} + 1/2\tau_{ij}}, & d\left(x_{ij}, C_j^{\text{max}}\right) > d\left(x_{ij}, C_j^{\text{min}}\right) \\ 0, & \text{other} \end{cases} \quad (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n), \tag{29}$$

$$\pi_{ij} = 1 - \mu_{ij} - \nu_{ij} \, (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n). \tag{30}$$

Then, all forms of values are converted to IFNs.

4.2. Entropy-GRA-ELECTRE III Integrated Evaluation Method. The cloud service selection approach using entropy weight and GRA-ELECTRE III under intuitionistic fuzzy environment is proposed. The entropy measure method extended to intuitionistic fuzzy environment is used to determine the weights of QoS attributes. In order to better reflect the relationship between alternatives and the positive point, GRA is used to modify the distance measure of ELECTRE III [53]. Moreover, due to the complexity of the distillation procedure of traditional ELECTRE III, the concepts of consistent credibility, inconsistent credibility, and net credibility are introduced to simplify the sorting process of cloud services [54]. Then the GRA-ELECTRE III integrated method under intuitionistic fuzzy environment is used to evaluate cloud services.

Suppose that a MCDM problem has m alternatives $A = \{A_1, A_2, \ldots, A_m\}$, and n decision criteria $C = \{C_1, C_2, \ldots, C_n\}$. Each alternative evaluated with respect to the n criteria form a decision matrix denoted by $X = (x_{ij})_{m\times n}$. Then the main steps of the proposed cloud service selection method can be described as follows:

Step 1: Obtain the decision matrix $X = (x_{ij})_{m\times n}$ of the decision maker, where x_{ij} can be described as crisp data, interval data, TFN, and IFN.

Step 2: Convert the value of cost criteria into benefit criteria and get the converted matrix $X' = (x'_{ij})_{m\times n}$ [39].

$$x'_{ij} = \begin{cases} x_j^{\max} - x_{ij}, & \text{criteria } j \text{ is crisp data} \\ \left[x_j^{\max} - b_{2ij}, x_j^{\max} - b_{1ij}\right], & \text{criteria } j \text{ is interval data} \\ \left(x_j^{\max} - a_{3ij}, x_j^{\max} - a_{2ij}, x_j^{\max} - a_{1ij}\right), & \text{criteria } j \text{ is TFN} \\ \left(\nu_{ij}, \mu_{ij}\right), & \text{criteria } j \text{ is IFN} \end{cases} \quad (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n). \tag{31}$$

In order to retain more evaluation information, $x_j^{\max}$ is defined as follows:

$$x_j^{\max} = \begin{cases} x_j^+, & \text{criteria } j \text{ is crisp data} \\ \left[b_{2j}^+, b_{2j}^+\right], & \text{criteria } j \text{ is interval data} \\ \left(a_{3j}^+, a_{3j}^+, a_{3j}^+\right), & \text{criteria } j \text{ isTFN} \end{cases} \quad (j = 1, 2, \ldots, n). \tag{32}$$

Step 3: Convert the value of matrix X' into IFNs by equations (20)–(30), and get the matrix $Y = (y_{ij})_{m\times n}$, $y_{ij} = (\mu_{ij}, \nu_{ij}, \pi_{ij})$.

Step 4: Calculate the weight by the entropy method extended to intuitionistic fuzzy environment [55].

$$e_j = -\frac{1}{m \ln 2} \sum_{i=1}^{m} \left(\mu_{ij} \ln \mu_{ij} + \nu_{ij} \ln \nu_{ij} - \left(1 - \pi_{ij}\right) \ln\left(1 - \pi_{ij}\right) - \pi_{ij} \ln 2\right), \tag{33}$$

where $0 \ln 0 \equiv 0$, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$.

Then d_j and w_j are calculated by equations (9) and (10).

Step 5: Obtain α, β, γ from users or experts.

Step 6: Calculate the grey relational coefficients between alternatives and the positive point in intuitionistic fuzzy environment by the following equation [53]:

$$\widetilde{y_{ij}} = \frac{\min_i \min_j d\left(y_{ij}, \alpha_j^+\right) + \rho \max_i \max_j d\left(y_{ij}, \alpha_j^+\right)}{d\left(y_{ij}, \alpha_j^+\right) + \rho \max_i \max_j d\left(y_{ij}, \alpha_j^+\right)}, \quad (i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n), \tag{34}$$

where ρ is usually equal to 0.5. The positive point defined as $\alpha_j^+ = (\mu_j^+, \nu_j^+, \pi_j^+)$, where $\mu_j^+ = \max \mu_j$, $\nu_j^+ = \min \nu_j$, $\pi_j^+ = 1 - \mu_j^+ - \nu_j^+$.

Step 7: Calculate concordance index $C(A_i, A_k)$ and the credibility score $S(A_i, A_k)$:

$$c_j(A_i, A_k) = \begin{cases} 0, if\ \widetilde{y_{kj}} \geq \widetilde{y_{ij}} + p_j 1, if\ \widetilde{y_{kj}} \leq \widetilde{y_{ij}} + q_j \dfrac{\widetilde{y_{ij}} + p_j - \widetilde{y_{kj}}}{p_j - q_j}, \end{cases} \quad \text{otherwise} \, (i = 1, 2, \ldots, m, \, k = 1, 2, \ldots, m, \, j = 1, 2, \ldots, n), \tag{35}$$

where the value of q_j, p_j, and ν_j are calculated by equations (11)–(14) based on $\widetilde{y_{ij}}$:

$$C(A_i, A_k) = \frac{\sum_{j=1}^{n} w_j \cdot c_j\left(y_{ij}, y_{kj}\right)}{\sum_{j=1}^{n} w_j}, \quad (i = 1, 2, \ldots, m, \, k = 1, 2, \ldots, m, \, j = 1, 2, \ldots, n). \tag{36}$$

Then, calculate the credibility score $S(A_i, A_k)$:

Table 2: Ratings of cloud service with respect to QoS attributes.

	C1	C2	C3	C4	C5
A1	126	[186, 285]	0.95	(0.5, 0.6, 0.7)	(0.65, 0.25)
A2	133	[180, 282]	0.88	(0.6, 0.8, 0.9)	(0.35, 0.60)
A3	110	[201, 291]	0.91	(0.6, 0.7, 0.9)	(0.85, 0.10)
A4	148	[197, 300]	0.87	(0.4, 0.6, 0.7)	(0.80, 0.10)
A5	107	[182, 280]	0.85	(0.3, 0.5, 0.7)	(0.30, 0.65)
A6	122	[195, 310]	0.96	(0.3, 0.4, 0.6)	(0.55, 0.35)
A7	140	[210, 330]	0.98	(0.4, 0.6, 0.9)	(0.50, 0.35)
A8	138	[197, 312]	0.93	(0.5, 0.7, 1.0)	(0.45, 0.50)

$$S(A_i, A_k) = \begin{cases} C(A_i, A_k), & \text{if } D_j(A_i, A_k) \le C(A_i, A_k) \\ C(A_i, A_k) \cdot \prod\limits_{D_j(A_i,A_k) > C(A_i,A_k)} \dfrac{1 - D_j(A_i, A_k)}{1 - C(A_i, A_k)}, & \text{otherwise}, \\ (i = 1, 2, \ldots, m,\ k = 1, 2, \ldots, m,\ j = 1, 2, \ldots, n). \end{cases} \tag{37}$$

where the $D_j(A_i, A_k)$ is the discordance index.

$$D_j(A_i, A_k) = \begin{cases} 0, & \text{if } \widetilde{y_{kj}} \le \widetilde{y_{ij}} + p_j \\ 1, & \text{if } \widetilde{y_{kj}} \ge \widetilde{y_{ij}} + v_j \\ \dfrac{\widetilde{y_{kj}} - p_j - \widetilde{y_{ij}}}{v_j - p_j}, & \text{otherwise} \end{cases} \quad (i = 1, 2, \ldots, m,\ k = 1, 2, \ldots, m,\ j = 1, 2, \ldots, n). \tag{38}$$

Step 8: Calculate the consistent credibility Φ_i^+, and it describes the degree that alternative $A_i\,(i = 1, 2, \ldots, m)$ is superior to other alternatives.

$$\Phi_i^+ = \sum S(A_i, A_k) \quad (i = 1, 2, \ldots, m,\ k = 1, 2, \ldots, m). \tag{39}$$

Calculate the consistent credibility Φ_i^-, it describes the degree that other alternatives are superior to alternative $A_i\,(i = 1, 2, \ldots, m)$.

$$\Phi_i^- = \sum S(A_k, A_i) \quad (i = 1, 2, \ldots, m, \quad k = 1, 2, \ldots, m). \tag{40}$$

Calculate the net credibility Φ_i.

$$\Phi_i = \Phi_i^+ - \Phi_i^- \quad (i = 1, 2, \ldots, m). \tag{41}$$

Step 9: Sort cloud services in descending order according to Φ_i.

5. Implementation and Experimental Results

In this simulation, a laptop manufacturer ABC submits the assembly task to the cloud manufacturing platform. Eight alternative cloud service providers {A1, A2, A3, A4, A5, A6, A7, A8} are interested in providing the required service. The proposed cloud service selection approach is used to evaluate eight alternative cloud services according to the QoS attributes shown in Table 1.

5.1. Experiment 1: Application of the Proposed Cloud Service Approach.

5.1. Experiment 1: Application of the Proposed Cloud Service Approach. The computational procedure of the proposed approach is summarized as the following steps:

Step 1: the decision matrix of the decision maker as shown in Table 2 is obtained.

Step 2: The values of cost criteria are converted into benefit criteria by equation (32) and the converted matrix as shown in Table 3 is obtained.

Step 3: The values of converted decision matrix are transformed into IFNs by equations (20)–(30). The results are shown in Table 4. The concrete calculation steps are shown in Appendix A.

Step 4: The relative weights of QoS attributes are calculated by equations (33), (9), and (10), and the results are shown in Table 5.

Step 5: In this case, $\alpha = 0.1$, $\beta = 3$, $\gamma = 0.6$ are obtained from experts.

Step 6: The grey relational coefficients between alternatives and the positive point calculated by equation (34) are shown in Table 6. Table 7 shows the positive points α_j^+.

Step 7: The concordance index and credibility score between alternatives are calculated by equations

Table 3: The converted decision matrix.

	C1	C2	C3	C4	C5
A1	22	[45, 144]	0.95	(0.5, 0.6, 0.7)	(0.65, 0.25)
A2	15	[48, 150]	0.88	(0.6, 0.8, 0.9)	(0.35, 0.60)
A3	38	[39, 129]	0.91	(0.6, 0.7, 0.9)	(0.85, 0.10)
A4	0	[30, 133]	0.87	(0.4, 0.6, 0.7)	(0.80, 0.10)
A5	41	[50, 148]	0.85	(0.3, 0.5, 0.7)	(0.30, 0.65)
A6	26	[20, 135]	0.96	(0.3, 0.4, 0.6)	(0.55, 0.35)
A7	8	[0, 120]	0.98	(0.4, 0.6, 0.9)	(0.50, 0.35)
A8	10	[18, 133]	0.93	(0.5, 0.7, 1.0)	(0.45, 0.50)

Table 4: The IFN decision matrix.

	C1	C2	C3	C4	C5
A1	(0.23, 0.00, 0.77)	(0.74, 0.00, 0.26)	(0.68, 0.00, 0.32)	(0.00, 0.52, 0.48)	(0.65, 0.25, 0.10)
A2	(0.00, 0.52, 0.48)	(0.79, 0.00, 0.21)	(0.00, 0.68, 0.32)	(0.74, 0.00, 0.26)	(0.35, 0.60, 0.05)
A3	(0.77, 0.00, 0.23)	(0.61, 0.00, 0.39)	(0.00, 0.24, 0.76)	(0.70, 0.00, 0.30)	(0.85, 0.10, 0.05)
A4	(0.00, 0.80, 0.20)	(0.39, 0.00, 0.61)	(0.00, 0.73, 0.27)	(0.00, 0.56, 0.44)	(0.80, 0.10, 0.10)
A5	(0.80, 0.00, 0.20)	(0.79, 0.00, 0.21)	(0.00, 0.80, 0.20)	(0.00, 0.70, 0.30)	(0.30, 0.65, 0.05)
A6	(0.52, 0.00, 0.48)	(0.00, 0.33, 0.67)	(0.73, 0.00, 0.27)	(0.00, 0.80, 0.20)	(0.55, 0.35, 0.10)
A7	(0.00, 0.71, 0.29)	(0.00, 0.80, 0.20)	(0.80, 0.00, 0.20)	(0.52, 0.00, 0.48)	(0.50, 0.35, 0.15)
A8	(0.00, 0.67, 0.33)	(0.00, 0.47, 0.53)	(0.48, 0.00, 0.52)	(0.71, 0.00, 0.29)	(0.45, 0.50, 0.05)

Table 5: The relative weights of QoS attributes.

	C1	C2	C3	C4	C5
e_j	0.37	0.38	0.36	0.34	0.84
d_j	0.63	0.62	0.64	0.66	0.16
w_j	0.23	0.23	0.24	0.24	0.06

Table 6: Grey relational coefficients.

	C1	C2	C3	C4	C5
A1	0.41	0.89	0.77	0.38	0.69
A2	0.36	1.00	0.35	1.00	0.44
A3	0.94	0.68	0.36	0.91	1.00
A4	0.33	0.50	0.34	0.37	0.89
A5	1.00	1.00	0.33	0.36	0.42
A6	0.59	0.37	0.86	0.34	0.59
A7	0.35	0.33	1.00	0.64	0.56
A8	0.35	0.37	0.56	0.92	0.50

Table 7: The positive point α_j^+.

	C1	C2	C3	C4	C5
α_j^+	(0.8, 0, 0.2)	(0.79, 0, 0.21)	(0.8, 0, 0.2)	(0.74, 0, 0.26)	(0.85, 0.1, 0.05)

Table 8: Concordance matrix.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	1.000	0.687	0.466	0.941	0.698	0.776	0.518	0.757
A2	0.703	1.000	0.709	0.941	0.768	0.486	0.732	0.762
A3	0.534	0.721	1.000	1.000	0.772	0.762	0.762	0.769
A4	0.515	0.529	0.295	1.000	0.540	0.530	0.518	0.518
A5	0.703	0.757	0.698	0.941	1.000	0.706	0.477	0.508
A6	0.751	0.529	0.238	0.831	0.540	1.000	0.625	0.757
A7	0.737	0.529	0.238	0.775	0.540	0.768	1.000	0.757
A8	0.475	0.755	0.482	0.831	0.540	0.514	0.760	1.000

Table 9: Credibility score matrix.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	1.000	0.000	0.000	0.941	0.000	0.776	0.518	0.000
A2	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.762
A3	0.000	0.721	1.000	1.000	0.772	0.000	0.000	0.769
A4	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000
A5	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
A6	0.000	0.000	0.000	0.831	0.000	1.000	0.625	0.000
A7	0.000	0.000	0.000	0.398	0.000	0.768	1.000	0.757
A8	0.000	0.000	0.000	0.000	0.000	0.507	0.000	1.000

Table 10: The consistent credibility, inconsistent credibility, and net credibility of alternatives.

	A1	A2	A3	A4	A5	A6	A7	A8
Φ_i^+	3.236	1.762	4.263	1.000	1.000	2.457	2.923	1.507
Φ_i^-	1.000	1.721	1.000	4.171	1.772	3.051	2.144	3.288
Φ_i	2.236	0.040	3.263	−3.171	−0.772	−0.594	0.779	−1.781

Table 11: The rank of alternatives.

	A1	A2	A3	A4	A5	A6	A7	A8
Rank	2	4	1	8	6	5	3	7

Table 12: Certain multiple for different scenarios.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
α	0.05	0.06	0.07	0.08	0.09	0.1
β	3	4.5	6	7.5	9	10
γ	0.5	0.6	0.7	0.8	0.9	1

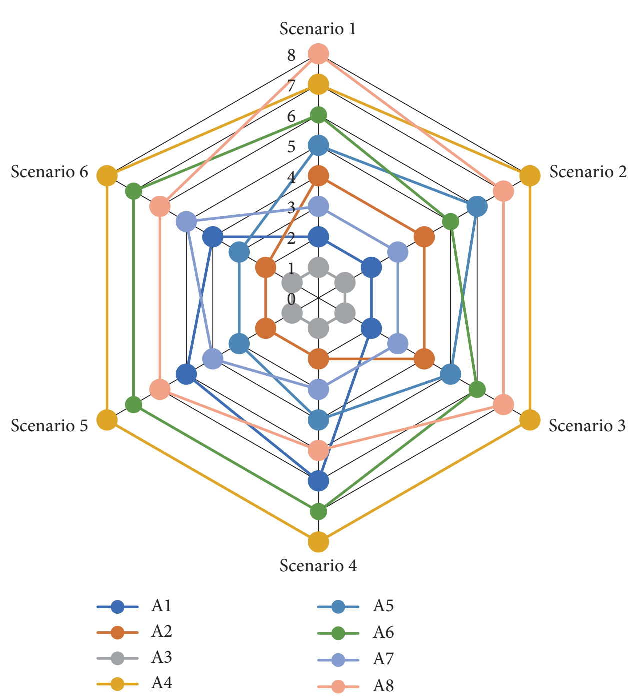

Figure 1: Experimental results under different scenarios. As shown in Figure 1, the following findings are obtained.

Table 13: Experimental results of comparative analysis.

	A1	A2	A3	A4	A5	A6	A7	A8
CC_i	0.640	0.557	0.754	0.296	0.495	0.514	0.481	0.515
Rank (TOPSIS)	2	3	1	8	6	5	7	4
Q_i	0.846	0.599	0.944	0.161	0.337	0.218	0.456	0.618
Rank (VIKOR)	1	4	1	8	6	7	5	3
Φ_i	2.236	0.040	3.263	−3.171	−0.772	−0.594	0.779	−1.781
Rank (ELECTRE III)	2	4	1	8	6	5	3	7

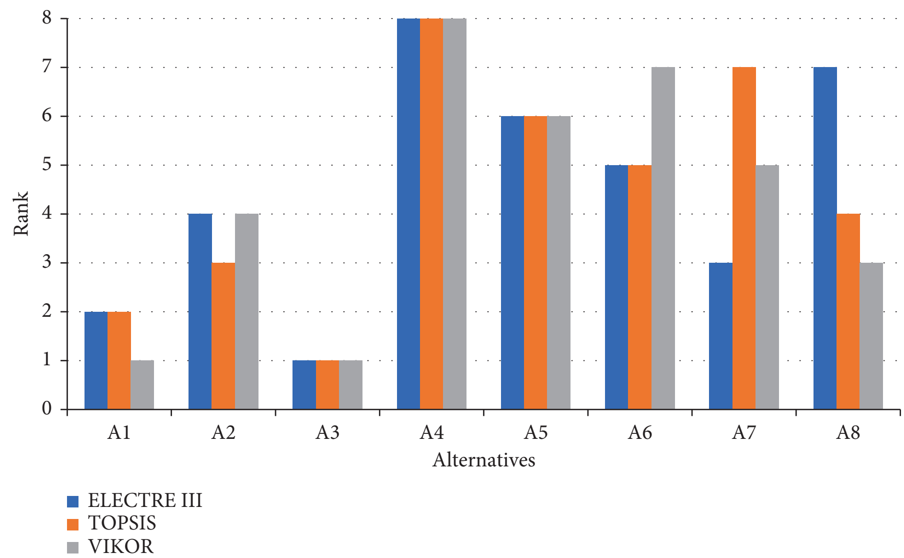

Figure 2: Experimental results of comparative analysis.

(35)–(38) as shown in Tables 8 and 9. The calculation steps are shown in Appendix B.

Step 8: The consistent credibility, inconsistent credibility, and net credibility are calculated by equations (39)–(41) as shown in Table 10.

Step 9: The ranks of cloud service providers are obtained according to Φ as shown in Table 11.

According to the rank of cloud services, alternative A3 is selected as the best one. Consequently, the proposed approach can effectively select the best cloud services under the heterogeneous environment of QoS attributes.

5.2. Experiment 2: Sensitivity Analysis. In order to verify the stability of the proposed cloud service approach and the effect of thresholds on the experimental results, additional experiments are carried out by adjusting the certain multiple α, β, γ of the thresholds. Multiple scenarios shown in Table 12 are carried out and the experimental results are shown in Figure 1.

Firstly, by adjusting certain multiple α, β, γ, the optimal cloud service has always been A3. This shows that the proposed approach has strong stability in the cloud service selection process.

Secondly, the ranking of intermediate alternatives has changed slightly. This shows that the proposed approach can reflect the preference of decision makers for certain multipliers.

In summary, the proposed cloud service selection approach has strong stability in cloud service selection process and can reflect the preference of decision makers.

5.3. Experiment 3: Comparative Analysis. To further validate the efficiency of the proposed cloud service selection approach, a comparative analysis experiment is executed. The two most popular compensatory methods, TOPSIS [56] and VIKOR [57], are adopted. This experiment is fed with the same assumptions and parameters as Experiment 1; for instance, the IFN decision matrix shown in Table 4 is used. In VIKOR, we use the distance between two IFNs to measure the difference. Table 13 and Figure 2 show the experimental results of these three methods TOPSIS, VIKOR, and ELECTRE III.

According to the experimental results shown in Figure 1, the following findings are obtained.

Firstly, the optimal cloud services selected by the three methods are consistent, which shows that the proposed approach is credible.

Secondly, experimental results show that the proposed approach has better discrimination and can better reflect the gap between alternatives.

In summary, the proposed cloud service selection approach is credible and has better discrimination.

Table 14: Quasi-satisfactory value (ξ).

	C1	C2	C3	C4
A1	22	[45, 144]	0.95	(0.45, 0.6, 0.8)
A2	20.5	[48, 150]	0.915	(0.6, 0.8, 0.9)
A3	38	[39, 129]	0.915	(0.6, 0.7, 0.9)
A4	20.5	[30, 133]	0.915	(0.45, 0.6, 0.8)
A5	41	[50, 148]	0.915	(0.45, 0.6, 0.8)
A6	26	[25, 135]	0.96	(0.45, 0.6, 0.8)
A7	20.5	[25, 135]	0.98	(0.4, 0.6, 0.9)
A8	20.5	[25, 135]	0.93	(0.5, 0.7, 1)

Table 15: Quasi-dissatisfactory value (ζ).

	C1	C2	C3	C4
A1	20.5	[25, 135]	0.915	(0.5, 0.6, 0.7)
A2	15	[25, 135]	0.88	(0.45, 0.6, 0.8)
A3	20.5	[25, 135]	0.91	(0.45, 0.6, 0.8)
A4	0	[25, 135]	0.87	(0.4, 0.6, 0.7)
A5	20.5	[25, 135]	0.85	(0.3, 0.5, 0.7)
A6	20.5	[20, 135]	0.915	(0.3, 0.4, 0.6)
A7	8	[0, 120]	0.915	(0.45, 0.6, 0.8)
A8	10	[18, 133]	0.915	(0.45, 0.6, 0.8)

Table 16: Quasi-uncertain value (η).

	C1	C2	C3	C4
A1	21.25	[35, 139.5]	0.9325	(0.475, 0.6, 0.75)
A2	17.75	[36.5, 142.5]	0.8975	(0.525, 0.7, 0.85)
A3	29.25	[32, 132]	0.9125	(0.525, 0.65, 0.85)
A4	10.25	[27.5, 134]	0.8925	(0.425, 0.6, 0.75)
A5	30.75	[37.5, 141.5]	0.8825	(0.375, 0.55, 0.75)
A6	23.25	[22.5, 135]	0.9375	(0.375, 0.5, 0.7)
A7	14.25	[12.5, 127.5]	0.9475	(0.425, 0.6, 0.85)
A8	15.25	[21.5, 134]	0.9225	(0.475, 0.65, 0.9)

Table 17: Quasi-membership degree (κ).

	C1	C2	C3	C4
A1	0.07	0.73	0.54	0.00
A2	0.00	0.95	0.00	0.73
A3	0.85	0.38	0.00	0.59
A4	0.00	0.16	0.00	0.00
A5	1.00	0.95	0.00	0.00
A6	0.27	0.00	0.69	0.00
A7	0.00	0.00	1.00	0.27
A8	0.00	0.00	0.23	0.62

Table 18: Quasi-nonmembership degree (ς).

	C1	C2	C3	C4
A1	0.00	0.00	0.00	0.27
A2	0.27	0.00	0.54	0.00
A3	0.00	0.00	0.08	0.00
A4	1.00	0.00	0.69	0.31
A5	0.00	0.00	1.00	0.59
A6	0.00	0.13	0.00	1.00
A7	0.61	1.00	0.00	0.00
A8	0.51	0.23	0.00	0.00

Table 19: Quasi-hesitancy degree (τ).

	C1	C2	C3	C4
A1	0.50	0.50	0.50	0.50
A2	0.50	0.50	0.50	0.50
A3	0.50	0.50	0.50	0.50
A4	0.50	0.50	0.50	0.50
A5	0.50	0.50	0.50	0.50
A6	0.50	0.50	0.50	0.50
A7	0.50	0.50	0.50	0.50
A8	0.50	0.50	0.50	0.50

Table 20: The values of q_j, p_j, and v_j.

	C1	C2	C3	C4	C5
q_j	0.07	0.07	0.07	0.07	0.06
p_j	0.20	0.20	0.20	0.20	0.17
v_j	0.40	0.40	0.40	0.40	0.35

Table 21: The results of $c_1(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	1.000	1.000	0.000	1.000	0.000	0.185	1.000	1.000
A2	1.000	1.000	0.000	1.000	0.000	0.000	1.000	1.000
A3	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A4	0.919	1.000	0.000	1.000	0.000	0.000	1.000	1.000
A5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A6	1.000	1.000	0.000	1.000	0.000	1.000	1.000	1.000
A7	1.000	1.000	0.000	1.000	0.000	0.000	1.000	1.000
A8	1.000	1.000	0.000	1.000	0.000	0.000	1.000	1.000

Table 22: The results of $c_2(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	1.000	0.694	1.000	1.000	0.694	1.000	1.000	1.000
A2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A3	0.000	0.000	1.000	1.000	0.000	1.000	1.000	1.000
A4	0.000	0.000	0.112	1.000	0.000	1.000	1.000	1.000
A5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A6	0.000	0.000	0.000	0.517	0.000	1.000	1.000	1.000
A7	0.000	0.000	0.000	0.269	0.000	1.000	1.000	1.000
A8	0.000	0.000	0.000	0.514	0.000	1.000	1.000	1.000

Table 23: The results of $c_3(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	1.000	1.000	1.000	1.000	1.000	0.855	0.000	1.000
A2	0.000	1.000	1.000	1.000	1.000	0.000	0.000	0.000
A3	0.000	1.000	1.000	1.000	1.000	0.000	0.000	0.031
A4	0.000	1.000	1.000	1.000	1.000	0.000	0.000	0.000
A5	0.000	1.000	1.000	1.000	1.000	0.000	0.000	0.000
A6	1.000	1.000	1.000	1.000	1.000	1.000	0.447	1.000
A7	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A8	0.000	1.000	1.000	1.000	1.000	0.000	0.000	1.000

Table 24: The results of $c_4(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	1.000	0.000	0.000	1.000	1.000	1.000	0.000	0.000
A2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A3	1.000	0.792	1.000	1.000	1.000	1.000	1.000	1.000
A4	1.000	0.000	0.000	1.000	1.000	1.000	0.000	0.000
A5	1.000	0.000	0.000	1.000	1.000	1.000	0.000	0.000
A6	1.000	0.000	0.000	1.000	1.000	1.000	0.000	0.000
A7	1.000	0.000	0.000	1.000	1.000	1.000	1.000	0.000
A8	1.000	0.929	1.000	1.000	1.000	1.000	1.000	1.000

Table 25: The results of $c_5(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1.000
A2	0.000	1.000	0.000	0.000	1.000	0.246	0.488	1.000
A3	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A4	1.000	1.000	0.540	1.000	1.000	1.000	1.000	1.000
A5	0.000	1.000	0.000	0.000	1.000	0.044	0.286	0.818
A6	0.639	1.000	0.000	0.000	1.000	1.000	1.000	1.000
A7	0.397	1.000	0.000	0.000	1.000	1.000	1.000	1.000
A8	0.000	1.000	0.000	0.000	1.000	0.726	0.968	1.000

Table 26: The results of $D_1(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000
A2	0.000	0.000	1.000	0.000	1.000	0.117	0.000	0.000
A3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A4	0.000	0.000	1.000	0.000	1.000	0.264	0.000	0.000
A5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A6	0.000	0.000	0.758	0.000	1.000	0.000	0.000	0.000
A7	0.000	0.000	1.000	0.000	1.000	0.205	0.000	0.000
A8	0.000	0.000	1.000	0.000	1.000	0.183	0.000	0.000

Table 27: The results of $D_2(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A3	0.050	0.587	0.000	0.000	0.587	0.000	0.000	0.000
A4	0.976	1.000	0.000	0.000	1.000	0.000	0.000	0.000
A5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A6	1.000	1.000	0.581	0.000	1.000	0.000	0.000	0.000
A7	1.000	1.000	0.746	0.000	1.000	0.000	0.000	0.000
A8	1.000	1.000	0.583	0.000	1.000	0.000	0.000	0.000

Table 28: The results of $D_3(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0.000	0.000	0.000	0.000	0.000	0.000	0.132	0.000
A2	1.000	0.000	0.000	0.000	0.000	1.000	1.000	0.036
A3	1.000	0.000	0.000	0.000	0.000	1.000	1.000	0.000
A4	1.000	0.000	0.000	0.000	0.000	1.000	1.000	0.068
A5	1.000	0.000	0.000	0.000	0.000	1.000	1.000	0.111
A6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A8	0.090	0.000	0.000	0.000	0.000	0.520	1.000	0.000

Table 29: The results of $D_4(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0.000	1.000	1.000	0.000	0.000	0.000	0.336	1.000
A2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A4	0.000	1.000	1.000	0.000	0.000	0.000	0.352	1.000
A5	0.000	1.000	1.000	0.000	0.000	0.000	0.443	1.000
A6	0.000	1.000	1.000	0.000	0.000	0.000	0.518	1.000
A7	0.000	0.815	0.343	0.000	0.000	0.000	0.000	0.435
A8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 30: The results of $D_5(A_i, A_k)$.

	A1	A2	A3	A4	A5	A6	A7	A8
A1	0.000	0.000	0.789	0.149	0.000	0.000	0.000	0.000
A2	0.410	0.000	1.000	1.000	0.000	0.000	0.000	0.000
A3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A5	0.545	0.000	1.000	1.000	0.000	0.000	0.000	0.000
A6	0.000	0.000	1.000	0.723	0.000	0.000	0.000	0.000
A7	0.000	0.000	1.000	0.884	0.000	0.000	0.000	0.000
A8	0.090	0.000	1.000	1.000	0.000	0.000	0.000	0.000

6. Conclusions

In this paper, a new hybrid MCDM approach is proposed to deal with cloud service selection problem. Firstly, the heterogeneous data of QoS attributes involving in cloud service selection process are handled, by converting crisp data, interval data, TFN and IFN into IFNs. Secondly, the weights of QoS attributes are calculated objectively by the extended entropy measure method in intuitionistic fuzzy environment. Finally, a more concise GRA-ELECTRE III integrated method in intuitionistic fuzzy environment is proposed to evaluate cloud services. The proposed cloud service selection approach performs well in dealing with the subjectivity, vagueness, and uncertainty of QoS attributes. Moreover, the proposed approach can effectively avoid mutual compensation between QoS attributes and reflect the weak preferences and indifference among alternatives. In future, more effectors will be carried out to explore interrelationships between QoS attributes. Moreover, the proposed cloud service selection approach will be utilized in other industrial cases, such as manufacturing industry, tourist industry, e-business, and so on to further improve its practicability.

Appendix

A. Intuitionistic Fuzzy Number Conversion

This appendix shows the calculation steps of convert the benefit decision matrix into IFN decision matrix under C1–C4.

Step 1: The Quasi-satisfactory value (ξ), Quasi-dissatisfactory value (ζ), and Quasi-uncertain value (η) are calculated as shown in Tables 14–16.

Step 2: The Quasi-membership degree (κ), Quasi-nonmembership degree (ς), and Quasi-hesitancy degree (τ) are calculated as shown in Tables 17–19.

Step 3: Then all forms of data are converted to IFNs as shown in Section 5.1.

B. Concordance Index and Credibility Score Calculation

This appendix shows the calculation steps of the concordance index and credibility score between alternatives.

Step 1: The value of q_j, p_j, and v_j are calculated are shown in Table 20.

Step 2: $c_j(A_i, A_k)$ under each criteria are calculated as shown in Tables 21–25.

Step 3: $c_j(A_i, A_k)$ are weighted and concordance index $C(A_i, A_k)$ are obtained as shown in Table 8.

Step 4: The discordance index $D_j(A_i, A_k)$ under each criteria are calculated as shown in Tables 26–30.

Step 5: The credibility score $S(A_i, A_k)$ are obtained as shown in Table 9.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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