An Improved CoCoSo Method with a Maximum Variance Optimization Model for Cloud Service Provider Selection

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With the rapid growth of available online cloud services and providers for customers, the selection of cloud service providers plays a crucial role in on-demand service selection on a subscription basis. Selecting a suitable cloud service provider requires a careful analysis and a reasonable ranking method. In this study, an improved combined compromise solution (CoCoSo) method is proposed to identify the ranking of cloud service providers. Based on the original CoCoSo method, we analyze the defects of the final aggregation operator in the original CoCoSo method which ignores the equal importance of the three subordinate compromise scores, and employ the operator of "Linear Sum Normalization" to normalize the three subordinate compromise scores so as to make the results reasonable. In addition, we introduce a maximum variance optimization model which can increase the discrimination degree of evaluation results and avoid inconsistent ordering. A numerical example of the trust evaluation of cloud service providers is given to demonstrate the applicability of the proposed method. Furthermore, we perform sensitivity analysis and comparative analysis to justify the accuracy of the decision outcomes derived by the proposed method. Besides, the results of discrimination test also indicate that the proposed method is more effective than the original CoCoSo method in identifying the subtle differences among alternatives.

Keywords: Multi-Criteria Decision Making; Cloud Service Provider Selection; Combined Compromise Solution (Cocosos); Maximum Variance; Discrimination Degree.

Introduction

Cloud computing is an emerging technology for providing software, platform and infrastructural resources on demand over the Internet, enabling consumers to avoid initial expenses, reduce operating costs, and enhance responses by acquiring the services and infrastructural resources instantaneously in an elastic manner, so that consumers can focus more time on innovation and the creation of business value. With the rapid development of cloud computing, cloud service providers (CSPs) such as Amazon, Google, Microsoft have launched a wide variety of cloud services, which allows consumers to handle large datasets running on remote servers (i.e., cloud) without installing and executing on local computers anymore (Varghese & Buyya, 2018). However, with the rapid growth of available online cloud services and providers, it becomes a challenge for consumers to choose the best service provider based on their operational requirements, financial constraints and long-term performance (Al-Faifi et al., 2019; Alshehri, 2019; Buyukozkan et al., 2018).

Selecting a suitable CSP requires a careful analysis and a reasonable ranking method. It can be viewed as a multi-criteria decision-making (MCDM) problem since it involves the intrinsic relationships among the quality of service (QoS) criteria. The studies on the CSP selection based on MCDM have gained huge momentum in recent years (Alabool et al., 2018). For example, the SAW (Simple Additive Weighting) was widely adopted for cloud service selection (Zhao et al., 2012; Qu et al., 2013). However, the SAW is a simple weighting approach that was generally used to solve single dimensional decision problems requiring low decision accuracy. Garg et al. (2013) proposed a cloud service quality
ranking method based on the AHP (Analytic Hierarchy Process). Choi and Jeong (2014) gave a quality evaluation method for cloud computing service selection based on the ANP (Analytic Network Process). Nawaz et al. (2018) applied the BWM (Best-Worst Method) for cloud service selection. Sidu and Singh (2019) proposed a PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations)-based method for the selection of trustworthy cloud database servers. Abourezq and Idrissi (2014) applied the ELECTRE (Elimination etchoix traduisant la realite)-based method to determine which cloud service meets the best users’ requirements. Costa et al. (2013) proposed an MCDM method for evaluating cloud services based on the MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique). However, these methods involve pairwise comparisons, which are complex and time-consuming, and are not suitable for the situation with large number of criteria and alternatives.

For solving the MCDM problem of cloud service selection, it is needed to deal with the compromise of QoS values of cloud services with respect to different or even conflicting evaluation criteria. In many cases, the decision-making process can be aided by a comprehensive analysis from the perspective of the basic properties of non-inferior or compromise solutions (Yu, 1973). At present, MCDM methods of cloud service selection have been researched to find a compromise solution. For example, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) was suggested by Singh and Sidhu (2017) to determine the trustworthiness degrees of cloud service providers based on a compromise solution. Serrai et al. (2016) exploited the VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje), which determines a compromise solution with a maximum group utility value and a minimum ‘individual’ regret value to rank the obtained skyline web services. Buyukozkan et al. (2018) proposed an integrated framework based on the AHP, VIKOR, MULTIMOORA (Multi-Objective Optimization on the basis of a Ratio Analysis plus the full MULTlPlicative form) and COPRAS (Complex Proportional Assessment) to select the most desirable cloud computing technology provider, which deduces a compromise solution with the maximum value of the sum of maximum weighted normalization criteria values and the minimum value of the sum of minimum weighted normalization criteria values. However, when using these methods to solve MCDM problems, the ranking results produced by these methods may change greatly corresponding to the change of weight distributions of criteria. In other words, the reliability and stability of the results produced by these methods are limited (Wen et al., 2019). To improve this limitation, the CoCoSo (Combined Compromise Solution) method, one of the MCDM methods, was proposed by Yazdani et al. (2019b). It integrates the SAW (Afshari et al., 2010), WASPAS (Weighted Aggregated Sum Product Assessment) (Zavadskas et al., 2012) and MEW (Multiplicative Exponential Weighting) methods (Zanakis et al., 1998) with aggregation strategies. By this method, decision-makers can obtain a multi-faceted compromise solution, which is consistent with the solution obtained by other MCDM methods, such as the VIKOR (Opricovic, 1998), WASPAS (Zavadskas et al., 2012) and MOORA (Multi-Objective Optimization on the basis of Ratio Analysis) (Brauers & Zavadskas, 2006) methods. Moreover, the optimal solution screened by the CoCoSo method is not easily affected by the changes of weight distribution of criteria or the deletion/addition of alternatives. These imply that the CoCoSo method is a robust method, which has advantages in reliability and stability of the decision-making results. In addition, the CoCoSo method is easy to understand and has wide applicability, and thus has been extended to different circumstances to solve decision-making problems in various fields (Peng et al., 2019; Yazdani et al., 2019a; Wen et al., 2019).

However, to the best of our knowledge, there is no literature on the application of the CoCoSo method in CSP selection problem. Therefore, this study incorporates the CoCoSo method to evaluate the trustworthiness of CSPs based on available real sample dataset. We dedicate to achieving the following contributions:

1. We analyze the defects of the final aggregation operator in the original CoCoSo method which ignores the equal importance of the three subordinate compromise scores, and employ the operator of “Linear Sum Normalization” to normalize the three subordinate compromise scores to make the results reasonable;
2. We propose a new integration function based on a maximum variance optimization model to aggregate the three subordinate compromise scores obtained in the CoCoSo method, so as to increase the differentiation degree of evaluation results and avoid inconsistent ordering;
3. We apply the proposed new MCDM method to select the optimal CSP, and then highlight the advantages of the proposed method by the sensitive analysis, consistency comparison of ranking results, and discrimination test.

The rest of this paper is organized as follows. First, we introduce the preliminaries of this study. Next, we present the improved CoCoSo method with a maximum variance optimization model. Then, we present a case study that uses the Cloud Armor to analyze the efficiency and reliability based on executing the proposed method and comparing with other MCDM methods. Finally, a conclusion with directions for future work is provided.

Preliminaries

In this section, we briefly review the literature on the MCDM methods related to the CSP selection, and the implementation steps of the CoCoSo method and its extension. In addition, we summarize the common normalization methods.

Literature Review of the CSP Selection Based on MCDM Methods

In the past few years, the selection of CSPs based on MCDM methods has been widely concerned on the evaluation and identification of trustworthy CSPs. The MCDM methods used to select CSPs can be classified into four categories: single MCDM methods, fuzzy MCDM methods, hybrid MCDM methods, and fuzzy hybrid MCDM methods. Table 1 lists the related works in terms of these four categories.
From Table 1, we can see that most studies have focused on the use of preference ordering-based methods, such as the AHP, ANP and BWM, PROMETHEE, ELECTRE, and MACBETH. But these methods involve pairwise comparisons, and thus are complex and time-consuming, especially in the situation with large number of criteria and alternatives. In addition, we can also find that some utility value-based methods such as the TOPSIS, VIKOR, COPRAS have been used in solving the problem of CSP selection from the perspective of the basic properties of non-inferior or compromise solutions. These methods have the advantages of the simple calculation, easy to understand, and available of ranking set. But the ranking results produced by these methods may change due to the change of weight distributions of criteria. Therefore, a new CSP selection method should be developed as an effective evaluation synthesis technique to cover the shortage. **Outline of the CoCoSo method and its extensions**

Yazdani et al. (2019b) proposed the CoCoSo method to deduce compromise solutions for MCDM problems by integrated the SAW, WASPAS and MEW methods with aggregation strategies. After determining the alternatives \((A_1, A_2, \cdots, A_m)\) and the evaluation criteria \((C_1, C_2, \cdots, C_n)\), the steps of the CoCoSo method are given as below.

**Step 1.** Form the initial decision matrix \(X\) for \(m\) alternatives with respect to \(n\) criteria:

\[
X = \begin{bmatrix}
A_1 & x_{11} & x_{12} & \cdots & x_{1m} \\
A_2 & x_{21} & x_{22} & \cdots & x_{2m} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
A_m & x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
; i = 1, 2, \cdots, m ; j = 1, 2, \cdots, n . \tag{1}
\]

**Step 2.** Based on the idea that the desirability degrees of alternatives are related to the distances between alternatives and negative ideal solutions, we need to normalize the elements in the initial matrix. For “benefit” type criteria such as the CPU processing performance and the Disc storage performance in QoS criteria, the element \(r_{ij}\) in the normalized matrix \(R_{mn}\) are obtained by:

\[
r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{2}
\]

For “cost” type criteria such as the network latency and the cost on demand in QoS criteria, the element \(r_{ij}\) in the normalized matrix \(R_{mn}\) are obtained by:

\[
r_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{3}
\]

**Step 3.** Using Eqs. (4) and (5) to obtain the sum of weighted comparability sequence \(S_i\) and power-weighted comparability sequences \(P_i\) for each alternative, respectively:

| Category | MCDM Method(s) | Reference(s) |
|----------|----------------|--------------|
| Single MCDM | AHP | Garg et al., 2013; Ramachandran et al., 2014; Són et al., 2013 |
| | ANP | Choi & Jeong, 2014; Ergu & Peng, 2014 |
| | ELECTRE | Silas et al., 2012 |
| | MAUT (Multi-Attribute Utility Theory) | Ding et al., 2014 |
| | MACBETH | Costa et al., 2013 |
| | PAPRIKA (Potentially All Pairwise Rankings of All Possible Alternatives) | Alismaili et al., 2016 |
| | PROMETHEE | Sudhu & Singh, 2019 |
| | SAW | Zhao et al., 2012 |
| | TOPSIS | Ginting et al., 2017 |
| Fuzzy MCDM method | Fuzzy AHP & fuzzy logic model | Panoviov et al., 2018 |
| | IVIFS (Improved Interval-Valued Intuitionistic Fuzzy Sets) & WASPAS | Gireesha et al., 2020 |
| | IFS (Intuitionistic fuzzy set) & TOPSIS | Mu et al., 2014 |
| | TFN (Triangular fuzzy number) & AHP | Low & Chen, 2012 |
| | TFN & Fuzzy ANP | Le et al., 2014 |
| | TFN & BWM | Hussain et al., 2020 |
| | TFN & TOPSIS | Basu & Ghosh, 2018 |
| | TFN & VIKOR | Alaboo & Mahmood, 2013 |
| | TrFN(Trapezoidal Fuzzy Number) & SAW | Qu et al., 2013 |
| | TNN (Triangular Neutrosophic Numbers) & AHP | Abdel-Basset et al., 2018 |
| Hybrid MCDM method | AHP & cloud model | Yang et al., 2018 |
| | AHP & Cosine Maximization method | Alshehri, 2019 |
| | AHP & Logic Scoring | Atas & Gungor, 2014 |
| | AHP & TOPSIS | Singh & Sudhu, 2017 |
| | ANP & DEMATEL & TOPSIS | Alimardani et al., 2014 |
| | ANP & GRA (Gray Relational Analysis) & DEMATEL (Decision Making Trial And Evaluation Laboratory) | Huang et al., 2012 |
| | ELECTRE & Block-Nested Loop Algorithm | Aborsuez & Idnissi, 2014 |
| | BWM & VIKOR | Serra et al., 2016 |
| | BWM & Markov chain method | Nawaz et al., 2018 |
| Fuzzy Hybrid MCDM method | BSC (Balanced score card) & fuzzy Delphi & Fuzzy AHP | Lee & Seo, 2016 |
| | AHP and grey TOPSIS | Jatoth et al., 2019 |
| | TFN & AHP & WASPAS | Alam et al., 2018 |
| | Rough AHP and rough TOPSIS | Li et al., 2018 |
| | Fuzzy set theory & TOPSIS & Dempster-Shafer theory & Game Theory | Exposito et al., 2015 |
| | IVIFS & AHP & COPRAS & MULTIMOORA & TOPSIS | Buyukozkan et al., 2018 |

Table 1
\[ S_i = \sum_{j=1}^{m} (w_j r_{ij}), \text{ for } i = 1, 2, \ldots, m \]  
\[ P_i = \sum_{j=1}^{m} (r_{ij})^{\lambda} \text{, for } i = 1, 2, \ldots, m \]  

where \( w_j \) denotes the weight of the \( j \)th criterion and \( \sum_{j=1}^{m} w_j = 1 \).

**Step 4.** Based on the idea of the MULTIMOORA method (Brauers & Zavadskas, 2010), we can compute the relative priorities of alternatives by the aggregation strategies shown as Eqs. (6)-(8). Eq. (6) expresses the arithmetic mean of sums of the WSM (Weighted Sum Method) and WPM (Weighted Product Method) scores. Eq. (7) signifies a sum of relative scores of WSM and WPM compared to the worst cases. Eq. (8) computes a balanced score of WSM and WPM models. Three subordinate compromise scores are obtained to generate the performance scores of the alternatives.

\[ k_{ij} = \frac{S_i + P_i}{\sum_{i=1}^{n} (S_i + P_i)}, \text{ for } i = 1, 2, \ldots, m \]  
\[ k_{ij} = \frac{S_i}{\min P_i} + \frac{P_i}{\max P_i}, \text{ for } i = 1, 2, \ldots, m \]  
\[ k_{ij} = \frac{\lambda (S_i) + (1-\lambda) (P_i)}{\lambda \max S_i + (1-\lambda) \max P_i}, \text{ for } i = 1, 2, \ldots, m \]  

In Eq. (8), the value of \( \lambda \) (usually \( \lambda = 0.5 \)) is determined by decision-makers and \( 0 \leq \lambda \leq 1 \).

**Step 5.** The ranking of all alternatives is determined in descending order of the performance scores of the alternatives:

\[ k_i = (k_{i1}, k_{i2}, k_{i3})^{\frac{1}{3}} + \frac{1}{3} (k_{i1}, k_{i2}, k_{i3}) \text{, for } i = 1, 2, \ldots, m \]

The CoCoSo method is easy to understand and has wide applicability. It has been extended to solve decision-making problems in various fields. For example, Yazdani et al. (2019a) proposed a grey combined compromise solution (CoCoSo-G) method for the supplier selection in construction management. Peng et al. (2019) proposed a Pythagorean fuzzy CoCoSo method for 5G industry evaluation. Wen et al. (2019) proposed a hesitant fuzzy linguistic CoCoSo method for the selection of third-party logistics service providers in supply chain finance. Ecer et al. (2020) adopted the CoCoSo method to evaluate the sustainability performance of OPEC countries. Zolfani et al. (2019) proposed a structured framework for sustainable supplier selection based on the combined BWM-CoCoSo model.

### Normalization Methods

Converting all performance values of alternatives under each criterion into non-dimensional forms is a crucial step in most MCDM methods. Several normalization methods have been developed (Jahan & Edwards, 2015). Table 2 shows five well-known normalization techniques (Gardziejczyk & Zabicki, 2017).

| Normalization method | Benefit criteria | Cost criteria |
|----------------------|------------------|--------------|
| Standardization      | \( r_j = \frac{x_j - \bar{x}_j}{\sigma_j} \) | \( r_j = -\frac{x_j - \bar{x}_j}{\sigma_j} \) |
| Vector normalization | \( r_j = \frac{x_j}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \) | \( r_j = \frac{1 - x_j}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \) |
| Linear max normalization | \( r_j = \frac{x_j}{x_j} \) | \( r_j = \frac{1 - x_j}{x_j} \) |
| Linear max–min normalization method | \( r_j = \frac{x_j - x_j}{x_j - x_j} \) | \( r_j = \frac{x_j - x_j}{x_j - x_j} \) |
| Linear normalization sum-based method | \( r_j = \frac{\sum_{i=1}^{n} x_{ij}}{\sum_{i=1}^{n} x_{ij}} \) | \( r_j = \frac{1/x_j}{1/x_j} \) |

Note. The notations in Table 2 refer to \( r_j \): the normalized value of the \( i \)th alternative on the \( j \)th criterion; \( x_j \): the value of the \( i \)th alternative on the \( j \)th criterion; \( x_j' \): the maximum \( x_j \); \( x_j'' \): the minimum \( x_j \); \( \bar{x}_j = \sum x_j / n \); \( \sigma_j = \sqrt{\frac{\sum (x_j - \bar{x}_j)^2}{n}} \).

The linear normalization sum-based method is one of the most widely used normalization methods in classical MCDMs such as the AHP, SWARA and Entropy weighting method (Ahn, 2011). It has the following advantages (Lakshmi & Venkatesan, 2014): (1) it has less computation time and space complexity; (2) the normalized values reflect the relationships and differences among original evaluation values, simultaneously; (3) the change of original evaluation values has little effect on the dimensionless results. Therefore, we apply the linear normalization sum-based method in this study to transform the three subordinate compromise scores derived by the original CoCoSo method into the numbers in the interval (0,1), so as to eliminate the inconsistency of dimensions.

### The Combined Compromise Solution Method with Maximum Variance (MV-CoCoSo)

**Problem Statement**

In the original CoCoSo method, Yazdani et al. (2019b) adopted the hybrid integration operator, i.e., Eq. (9), to synthesize the advantages of the arithmetic average integration operator and geometric average integration operator. However, this integration takes the three subordinate compromise scores, which have great differences in scores, as equally important. For the three subordinate aggregation operators, i.e., Eqs. (6)-(8), it is not difficult to find that \( k_{ij} \in (0,1) \), \( k_{i2} > 1 \) and \( k_{i3} \in (0,1) \). If we use Eq. (9) to integrate them together, the value of \( k_{i2} \) will have a greater impact on the final result than those of \( k_{ij} \) and \( k_{i3} \), but in practice, \( k_{i2} \) may be the least important among the three subordinate compromise scores. This defect of the original CoCoSo was first pointed out by Wen et al. (2019), and they presented an improved CoCoSo
mehtod based on the ORESTE (Wu & Liao, 2018). However, the improved method is still limited in increasing the discrimination degree among alternatives to improve the recognition of results. To overcome the above limitation, we introduce the operator of “Linear Sum Normalization” to normalize the three subordinate compromise scores to make the aggregated results reasonable.

In addition, the purpose of MCDM method is to find out the differences among alternatives in terms of the advantages and disadvantages among alternatives. The great discrimination degree of scores regarding evaluation objects is more helpful in supporting decision making. Existing difference-driven comprehensive evaluation methods (Guo, 2012; Li et al., 2018; Ji et al., 2018) mainly depended on the determination of the weight coefficients to connect the original evaluation information and aggregated information. In fact, the calculated evaluation criteria weights can not maximize the overall differences among the evaluated objects, and only under the premise of linear weighting model can widen the difference among the evaluated objects. In this study, we learn from the scatter degree method (Guo, 2012) based on the maximum variance to establish a nonlinear programming model, so that we can aggregate the three subordinate compromise scores in the CoCoSo method and maximize the difference among the aggregated evaluation scores of each evaluation object. In this way, the improved CoCoSo method not only does not require decision-makers to give specific weights of the subordinate aggregation operators, but also can maximize the global and local differences among alternatives so as to increase the discrimination degree of the evaluation results and avoid the inconsistency ordering, which makes the decision-making process simple and efficient.

The Proposed Method

An improved CoCoSo method with a new integration function based on the nonlinear programming model with maximum variance is proposed as follows:

Steps 1–4. The same as Steps 1–4 in the original CoCoSo method.

Step 5. Apply the formula of “Linear Sum Normalization”, i.e., Eq. (10), to normalize the three subordinate compromise scores:

\[ k'_a = k_a / \sum_{h} k_a, \quad \text{for} \quad i = 1, 2, \ldots, m; \quad h = 1, 2, 3. \] (10)

where \( k_a \) is the evaluation score of the \( i \)-th alternative under the \( h \)-th aggregation strategy, \( k'_a \) is the normalized value of \( k_a \), such that \( k'_a \in [0,1] \) and \( \sum_{i} k'_a = 1 \).

Step 6. Construct the objective function and its constraints. To make the differences among the evaluated objects as large as possible, the overall difference of the evaluated objects can be measured by the variance of the comprehensive evaluation value of the evaluated objects:

\[ S^2 = \frac{1}{m} \sum_{i=1}^{m} (k'_i - \bar{k'})^2 \] (11)

where \( k'_i \) denotes the comprehensive score of each evaluation object after synthesizing the three normalized subordinate compromise scores.

Furthermore, using Eqs. (12) and (13), we can determine the reasonable range of the comprehensive score of each evaluated object:

\[ k'_i \in [k''_i, k'_i] \] (12)

\[ \sum_{i=1}^{m} k'_i = 1 \] (13)

where

\[ k''_i = \min \{k'_1, k'_2, k'_3\} \quad \text{and} \quad k'_i = \max \{k'_1, k'_2, k'_3\}. \]

According to Eq. (13), the mean of the comprehensive scores of all alternatives can be obtained by:

\[ \bar{k'} = (k''_1 + k''_2 + \cdots + k''_m) / m \] (14)

According to Eqs. (11) and (14), we can furtherly calculate the variance of comprehensive scores:

\[ S^2 = \frac{1}{m} \sum_{i=1}^{m} (k'_i - \bar{k'})^2 = \frac{1}{m} \sum_{i=1}^{m} k'_i - \frac{1}{m} \] (15)

Finally, we can construct an objective function and its constraint by synthesizing Eqs. (12)-(15) as following:

\[ \max \frac{1}{m} \sum_{i=1}^{m} (k'_i - \frac{1}{m})^2 \] (16)

\[ \sum_{i=1}^{m} k'_i = 1 \]

\[ k''_i \leq k'_i \leq k'_i \]

Step 7. Rank all the alternatives. The alternative with the maximum \( k'_i \) is chosen as the optimal alternative. The ranking of other available alternatives are determined in descending order of the values of \( k'_i \), for \( i = 1, 2, \ldots, m \).

Case study

In this section, a case study regarding the trustworthiness determination of CSPs is given, which shows the applicability of the proposed method. First, we briefly describe the background of the case. Second, we apply the proposed method to solve the problem. Finally, we test and validate the proposed method.

Case Description

Cloud Armor is a research project at the University of Adelaide, which aims to develop a scalable and robust trust management framework for cloud environment. It contains more than 10,000 feedbacks related to QoS criteria, which are provided by nearly 7,000 customers for 114 real-world cloud services. In this study, the sample dataset was extracted from the Cloud Armor project (Noor et al., 2015), which has been used by other scholars (Gireesha et al., 2020; Singh & Sidhu, 2017; Somu et al., 2017) to validate the accuracy, effectiveness, and feasibility of MCDM methods for CSP selection problem. The dataset consists of the performances of 15 CSPs on 9 QoS criteria. The benchmark criteria include: availability (A_r), response time (R), price (P), speed (S), storage space (S), features (F), ease of use (E), technical support (T) and customer service (C). All the criteria are assumed as beneficial criteria, and a five-point scale was used for the criteria in which the value “1” indicates the most insignificant feedback score while the value “5” indicates the most significant feedback score. In addition, the relative normalized weights of the QoS criteria are as follows: \( A_r = 0.1212, R = 0.1364, P_r = 0.1364, S_p = \)
Applying the MV-CoCoSo Method to Solve the Case

Step 1. From the dataset (Noor et al., 2015), a decision matrix with respect to 15 CSPs on 9 QoS criteria is obtained as shown in Table 3. Then, we normalize the initial decision matrix by Eq. (2), and the results are shown in Table 4.

Combined with the weight of each criterion, we can calculate the sum of the weighted comparability sequences and power-weighted comparability sequences by Eqs. (4) and (5), respectively. The vector of the sum of weighted comparability sequences for each CSP $S$ and the power-weighted comparability sequences for each CSP $P$ can be obtained as: $S = (0.9472, 0.9383, 0.3473, 0.7590, 0.9648, 1.0002, 0.7312, 0.9472, 0.6037, 0.4117, 0.2437, 0.9017, 0.3473, 0.9547, 0.8891)'$, $P = (8.9291, 8.9278, 6.3141, 8.6797, 8.9579, 9.0000, 8.6757, 8.9399, 8.4631, 7.4777, 5.4553, 8.8861, 6.4082, 8.9462, 8.8679)'$. Then, the three subordinate compromise scores are obtained by Eqs. (6)-(8). The results are shown in Table 5. Here we let $\lambda = 0.5$ in Eq. (8).

| CSP   | $A_i$ | $R_i$ | $P_i$ | $S_i$ | $S_k$ | $S_e$ | $E_k$ | $T_k$ | $C_i$ |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| CSP01 | 5     | 5     | 5     | 3     | 5     | 5     | 5     | 5     | 5     |
| CSP02 | 5     | 5     | 5     | 4     | 4     | 5     | 5     | 5     | 5     |
| CSP03 | 3     | 3     | 3     | 4     | 5     | 2     | 2     | 2     | 2     |
| CSP04 | 5     | 4     | 4     | 4     | 3     | 5     | 5     | 5     | 5     |
| CSP05 | 5     | 5     | 5     | 4     | 5     | 5     | 5     | 5     | 5     |
| CSP06 | 5     | 5     | 5     | 5     | 5     | 5     | 5     | 5     | 5     |
| CSP07 | 4     | 4     | 4     | 4     | 5     | 5     | 5     | 4     | 4     |
| CSP08 | 5     | 5     | 5     | 5     | 5     | 5     | 4     | 5     | 4     |
| CSP09 | 3     | 4     | 4     | 3     | 4     | 3     | 5     | 4     | 4     |
| CSP10 | 5     | 4     | 4     | 4     | 1     | 1     | 1     | 1     | 1     |
| CSP11 | 2     | 3     | 2     | 3     | 3     | 3     | 3     | 2     | 3     |
| CSP12 | 5     | 5     | 5     | 5     | 5     | 5     | 5     | 4     | 4     |
| CSP13 | 3     | 3     | 3     | 3     | 2     | 3     | 3     | 4     | 3     |
| CSP14 | 5     | 5     | 4     | 5     | 5     | 5     | 5     | 5     | 5     |
| CSP15 | 5     | 5     | 4     | 5     | 4     | 5     | 5     | 5     | 5     |

Step 2. After obtained the results of three subordinate aggregation operators, the three subordinate compromise scores $k_{ii}$, $k_{ij}$ and $k_{ji}$ are normalized using Eq. (10).

Step 3. We construct objective function and its constraints based on Eq. (16). By LINGO 17.0 software package, we can produce the comprehensive score of each CSP $k^{*}_i$. The final ranks can be gained accordingly as shown in Table 6. From Table 6, it is evident that CSP06 ($k^{*}_i = 0.0852$) is determined to be the most trustworthy service provider. In contrast, CSP11 ($k^{*}_i = 0.0305$) is determined to be the least trustworthy service provider.

Test and Validation of the Proposed Method

In this section, the performances of the MV-CoCoSo method are tested and validated from three aspects: sensitivity analysis, results consistency comparison, and discrimination test.
Sensitivity Analysis

We perform sensitivity analysis to validate the results and justify the accuracy and deviation of the decision outcomes derived by the proposed method. The sensitivity analysis can help decision-makers understand the robustness of the method by changing the data. Here, we perform two sensitivity tests.

First, we adopt the weight replacement strategy for sensitivity test. Since some criteria have the same weight, we exclude the case that the weights of criteria are still the same after the exchange. Finally, there are 28 different experiments being conducted. The weight information of each criterion in each experiment is shown in Table 7. For each experiment, the $k^*_{v}$ values are obtained and a different name is given to each calculation. For example, $A_{r}-R_{r}$ denotes that the weights of criterion $A_{r}$ and criterion $R_{r}$ are interchanged. Figure 1 shows the results of the experiment of sensitivity analysis on the criteria weights. From Figure 1, it is clear that CSP06 ranks the first and CSP11 ranks the last in all experiments, and the second-best CSP is CSP05 in the 25 experiments out of 28 experiments. As a whole, there are few deviations in other CSPs. Therefore, for the obtained results, it is obvious that our decision-making model is robust and rarely sensitive to the criteria weights. In addition, according to Eq. 8 (in Step 4) in the proposed algorithm, we can find that the effect of eventual ranking can be related to $\lambda$. Therefore, we perform a sensitivity analysis based on the change of the value of $\lambda$ in the range from 0 to 1. From Table 8, it is clearly seen that for the change of $\lambda$ value, there is no change in the final ranking obtained by the proposed method throughout the analysis. Therefore, it can be concluded that the final ranking results are reliable and robust based on the sensitivity analysis.

The Consistency Comparison of Ranking Results

Based on the ranking results, we also compare the proposed method with other MCDM methods, involving the WASPAS (Zavadskas et al., 2012), VIKOR (Opricovic, 1998), TOPSIS (Ginting et al., 2017), CODAS (Keshavarz Ghorabaee et al., 2016), and the original CoCoSo method (Yazdani et al., 2019b), as shown in Table 9.

From Table 9, we can find that the results obtained by the proposed approach have high degrees of similarity with those deduced by other MCDM methods. In particular, the top three alternatives selected by the proposed method are completely consistent with other MCDM methods. In addition, we adopt the Spearman’s rank correlation coefficients (Liao & Wu, 2020) to compare the ranking results obtained by different techniques. The correlation coefficient ($CC$) is between -1 and 1. The larger value indicates the stronger correspondence of the compared rankings. If $CC \geq 0.8$, the relationship between variables is considered high. In this regard, the proposed method is in a significant consistent with the other five applied methods (Table 10). We can see that all the Spearman’s rho correlation coefficient values are significant at the 0.01 level of significance. Especially, we can find that the lowest correlation coefficient ($\rho$) of the proposed method is higher than that of other methods from the bold part of Table 10 (expect for the original CoCoSo method, because the proposed method and the original CoCoSo method have the same ranking result). Meanwhile, the average correlation coefficient ($\rho$) of each method also be calculated as follows: $\rho = 0.987, 0.977, 0.978, 0.982, 0.981$. These results imply a high reliability of our method.
Experiments for Weight Sensitivity Analysis

| CSP   | λ=0.0 | λ=0.1 | λ=0.2 | λ=0.3 | λ=0.4 | λ=0.5 | λ=0.6 | λ=0.7 | λ=0.8 | λ=0.9 | λ=1 |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----|
| CSP01 | 5     | 5     | 5     | 5     | 5     | 5     | 5     | 5     | 5     | 5     | 5   |
| CSP02 | 6     | 6     | 6     | 6     | 6     | 6     | 6     | 6     | 6     | 6     | 6   |
| CSP03 | 13    | 13    | 13    | 13    | 13    | 13    | 13    | 13    | 13    | 13    | 13  |
| CSP04 | 9     | 9     | 9     | 9     | 9     | 9     | 9     | 9     | 9     | 9     | 9   |
| CSP05 | 2     | 2     | 2     | 2     | 2     | 2     | 2     | 2     | 2     | 2     | 2   |
| CSP06 | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1   |
| CSP07 | 10    | 10    | 10    | 10    | 10    | 10    | 10    | 10    | 10    | 10    | 10  |
| CSP08 | 4     | 4     | 4     | 4     | 4     | 4     | 4     | 4     | 4     | 4     | 4   |
| CSP09 | 11    | 11    | 11    | 11    | 11    | 11    | 11    | 11    | 11    | 11    | 11  |
| CSP10 | 14    | 14    | 14    | 14    | 14    | 14    | 14    | 14    | 14    | 14    | 14  |
| CSP11 | 15    | 15    | 15    | 15    | 15    | 15    | 15    | 15    | 15    | 15    | 15  |
| CSP12 | 7     | 7     | 7     | 7     | 7     | 7     | 7     | 7     | 7     | 7     | 7   |
| CSP13 | 12    | 12    | 12    | 12    | 12    | 12    | 12    | 12    | 12    | 12    | 12  |
| CSP14 | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3   |
| CSP15 | 8     | 8     | 8     | 8     | 8     | 8     | 8     | 8     | 8     | 8     | 8   |

The Experiment Results of Sensitivity Analysis of the Parameter λ

Discrimination Test

Decision-makers evaluate an alternative by various methods, mainly relying on the final scores of alternatives. If there is a large gap among the scores of different alternatives, it is easy to determine the ranking of alternatives. Otherwise, it is somewhat difficult to rank when the gap among these scores is small. In this sense, we perform a discrimination test to verify the discrimination degree of the proposed methods from the local and global points of view.

The Ranking Comparison between the Proposed Method and other MCDM Methods

Table 9

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Table 10

Numerical Results of Spearman’s Rho Test of Correlation Significance of Ranks between the Compared Methods

| Spearman’s rho | MV-CoCoSo | CoCoSo | TOPSIS | VIKOR | WASPAS | CODAS |
|---------------|-----------|--------|--------|-------|--------|-------|
| MV-CoCoSo     | Correlation Coefficient | 1.000  | 1.000** | .975** | .986** | .982** | .979** |
| CoCoSo        | Correlation Coefficient | 1.000** | 1.000  | .975** | .986  | .982** | .979  |
| TOPSIS        | Correlation Coefficient | .975**  | .975** | 1.000  | .961** | .982** | .968** |
| VIKOR         | Correlation Coefficient | .986**  | .986** | .961** | 1.000  | .982** | .971** |
| WASPAS        | Correlation Coefficient | .982**  | .982** | .961** | 1.000  | .986  | 1.000  |
| CODAS         | Correlation Coefficient | .979**  | .979** | .968** | .971  | .986** | 1.000  |

Note: ** denotes the correlation was significant at 0.01 level (double tail).

Figure 1. Results of the Sensitivity Analysis on the Criteria Weights

To test the local discrimination degree, we compare the proposed method with the original CoCoSo method by Eq. (17), which uses the relative deviation (Ke et al., 2007) to demonstrate the improvement of the proposed method in terms of the discrimination degree:

\[ \eta = \frac{\alpha_{\text{max}} - \alpha_{\text{sec}}}{\alpha_{\text{max}}} \times 100\% \]  \hspace{1cm} (17)

where \( \alpha_{\text{max}} \) and \( \alpha_{\text{sec}} \) denote the final scores of the alternatives that rank at the first preferred position and the second preferred position. \( \eta \) denotes the relative deviation between the first preferred alternative and the second preferred alternative. The higher \( \eta \) is, the better the method is in discrimination.

Suppose that \( A_i \) (\( i = 1, 2, \ldots, m \)) are alternatives, \( D_t \) (\( t = 1, 2, \ldots, q \)) are decision-making methods, the values for the alternatives obtained by different methods are \( h_{ij} \) \((i = 1, \ldots, m; t = 1, \ldots, q)\). To test the global discrimination degree of each method, the discrimination ability index \( Q_t \) could be built as (Ma, 2019):

\[ \mu_t = \frac{1}{m} \sum_{i=1}^{m} h_{ij}, \ t = 1, 2, \ldots, q \]  \hspace{1cm} (18)

\[ \lambda_t = \sum_{j=1}^{q} \left| h_{ij} - H_j \right|, \ t = 1, 2, \ldots, q \]  \hspace{1cm} (19)

\[ Q_t = \frac{\lambda_t}{\mu_t}, \ t = 1, 2, \ldots, q \]  \hspace{1cm} (20)

where \( Q_t \) reflects the discrimination ability of alternative \( A_i \) ranked by \( D_t \). The higher \( Q_t \) is, the better the method is in discrimination.
The original CoCoSo method is from Yazdani et al., 2019 of Chongqing Technology and Business University under Grant No.2015-56-01.

Table 11

The Dataset of a Logistic Provider Selection in the Original CoCoSo Method (Yazdani et al., 2019)

| Alternatives | C1 | C2 | C3 | C4 | C5 |
|--------------|----|----|----|----|----|
| Criteria     | Benefit | Cost | Benefit | Benefit | Benefit |
| Weights      | 0.036 | 0.192 | 0.326 | 0.326 | 0.12 |
| A1           | 60  | 0.4 | 2,540 | 500  | 990 |
| A2           | 6.35 | 0.15 | 1,016 | 3,000 | 1,041 |
| A3           | 6.8 | 0.1 | 1,727.2 | 1,500 | 1,676 |
| A4           | 10 | 0.2 | 1,000 | 2,000 | 965 |
| A5           | 2.5 | 0.1 | 560 | 500 | 915 |
| A6           | 4.5 | 0.08 | 1,016 | 350 | 508 |
| A7           | 3  | 0.1 | 1,778 | 1,000 | 920 |

By Eq. (17), we can obtain that the $\eta$ of the proposed method is 2.58%, while the $\eta$ of the original CoCoSo method is 2.07% in this case study. In addition, by Eq. (18)-(20), we can obtain that the $Q$ of the proposed method is 37.83, while the $Q$ of the original CoCoSo method is 30.24. Thus, we can conclude that, compared with the original CoCoSo method, the proposed method is easier to make final decision.

We also use the dataset associated with the original CoCoSo method (Yazdani et al., 2019) to validate the performance of the proposed algorithm. The dataset was related to a logistic provider selection problem, as displayed in Table 11.

Table 12 gives the final scores and ranks of each alternative derived by the proposed method and the original CoCoSo method. From Table 12, we can find that the proposed method has the same ranking results as those derived by the original CoCoSo method. However, the $\eta$ of the proposed method is 3.66%, while the $\eta$ of the original CoCoSo method is 3.26%; the $Q$ of the proposed method is 6.07, while the $Q$ of the original CoCoSo method is 5.75. Hence, it can be concluded that the discrimination ability of alternatives ranking of the proposed method is superior to the original CoCoSo method from the local and global perspectives.

Table 12

The Ranking Results of MV-CoCoSo and Original CoCoSo Method

| Alternatives | $k_{i1}$ | $k_{i2}$ | $k_{i3}$ | CoCoSo | MV-CoCoSo |
|--------------|---------|---------|---------|--------|----------|
|              | $k_i$   | Rank |        |        | $k_i^*$ | Rank |
| A1           | 0.131   | 3.245 | 0.724  | 2.041  | 5       | 0.131 | 5 |
| A2           | 0.175   | 4.473 | 0.973  | 2.788  | 2       | 0.184 | 2 |
| A3           | 0.18    | 4.64  | 1      | 2.882  | 1       | 0.191 | 1 |
| A4           | 0.163   | 3.721 | 0.906  | 2.416  | 4       | 0.154 | 4 |
| A5           | 0.088   | 2     | 0.487  | 1.299  | 7       | 0.082 | 7 |
| A6           | 0.097   | 2.225 | 0.54   | 1.443  | 6       | 0.092 | 6 |
| A7           | 0.165   | 3.951 | 0.915  | 2.519  | 3       | 0.165 | 3 |

Conclusions

In this study, we proposed an improved CoCoSo method for the CSP selection. The final aggregation operator in the original CoCoSo method takes the equal importance of the three subordinate compromise scores. To avoid this defect, we introduced the “Linear Sum Normalization” to normalize the three subordinate compromise scores so as to make the aggregated results reasonable. In addition, we introduced a nonlinear programming model with variance maximization to aggregate the three subordinate compromise scores and maximize the divergence among the aggregated scores of each evaluation object. The proposed method can avoid contradictory and increase the discrimination degree of evaluation results, so as to help decision-makers select the optimal CSP. To prove the advantages of the proposed method, a numerical example of the trust evaluation of CSPs was conducted based on the synthetic and real cloud data derived from the Cloud Armor project. By sensitive analysis, the stability of the proposed model was approved. The ranking results were highly consistent with those deduced by other existing decision-making methods. Furthermore, the results of discrimination test also indicated that the proposed method is more effective than the original CoCoSo method to identify the subtle difference among alternatives.

Our future work will focus on extending this algorithm by Z-numbers and D-numbers to support MCDM for handling information reliability problems involved in the decision-making process and enhance evidential reasoning ability for increasing the accuracy of CSP selection. In addition, we intend to further optimize our approach and explore its applicability in renewable energy investment and green economy development. Since the essence of a green economy is the sustainable development of the economy with the coordinated development of both ecology and economy, it needs to consider multiple conflicting criteria, which will lead to inaccessibility of utopia alternatives.

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