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Sustainable Cloud Service Provider Development by a Z-Number-Based DNMA Method with Gini-Coefficient-Based Weight Determination

Han Lai [1,2], Huchang Liao [2,3,*], Jonas Šaparauskas [4], Audrius Banaitis [4], Fernando A. F. Ferreira [5,6] and Abdullah Al-Barakati [3]

1 Chongqing Engineering Laboratory for Detection, Control and Integrated System, Chongqing Technology and Business University, Chongqing 400067, China; laihan_ctbu@126.com
2 Business School, Sichuan University, Chengdu 610064, China
3 Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia; aaalbarakati@kau.edu.sa
4 Department of Construction Management and Real Estate, Vilnius Gediminas Technical University, Vilnius LT-10223, Lithuania; jonas.saparauskas@vgtu.lt (J.Š.); audrius.banaitis@vgtu.lt (A.B.)
5 ISCTE Business School, BRU-IUL, University Institute of Lisbon, Avenida das Forças Armadas, 1649-026 Lisbon, Portugal; fernando.alberto.ferreira@iscte.pt
6 Fogelman College of Business and Economics, University of Memphis, Memphis, TN 38152-3120, USA
* Correspondence: liaohuchang@scu.edu.cn; Tel.: +86-177-7161-1031

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Abstract: The sustainable development of cloud service providers (CSPs) is a significant multiple criteria decision making (MCDM) problem, involving the intrinsic relations among multiple alternatives, (quantitative and qualitative) decision criteria and decision-experts for the selection of trustworthy CSPs. Most existing MCDM methods for CSP selection incorporated only one normalization technique in benefit and cost criteria, which would mislead the decision results and limit the applications of these methods. In addition, these methods did not consider the reliability of information given by decision-makers. Given these research gaps, this study introduces a Z-number-based double normalization-based multiple aggregation (DNMA) method to tackle quantitative and qualitative criteria in forms of benefit, cost, and target types for sustainable CSP development. We extend the original DNMA method to the Z-number environment to handle the uncertain and unreliability information of decision-makers. To make trade-offs between normalized criteria values, we develop a Gini-coefficient based weighting method to replace the mean-square-based weighting method used in the original DNMA method to enhance the applicability and isotonicity of the DNMA method. A case study is conducted to demonstrate the effectiveness of the proposed method. Furthermore, comparative analysis and sensitivity analysis are implemented to test the stability and applicability of the proposed method.

Keywords: multiple criteria decision making; sustainable development; cloud service provider selection; double normalization-based multiple aggregation (DNMA) method; Z number; Gini coefficient

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1. Introduction

Today's organizations, regardless of their size and business scope, pay more and more attention to the maintenance of competitiveness and the establishment of a sustainable environment [1]. World Commission on Environment and Development of the United Nations Brundtland defined sustainability development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [2]. Sustainability requires sustainable business practices. For doing so, information systems play an important role in the organization transition towards sustainability initiatives. The sustainable information systems have been considered as an opportunity for organizations to improve productivity, reduce costs, and increase profitability [3]. The flexible, elastic and agile nature of cloud computing provides an opportunity for governmental, academic and business organizations to consider migrating their existing applications to cloud environments to make their business processes agile with minimal cost and management effort [4]. Due to the increase in the number of cloud service providers (CSPs) offering functionally similar cloud services with varying cost, features and quality, it becomes extremely complex and burdensome to select a dependable, scalable, sustainable and high cost-effective cloud service for consumers to fulfil and satisfy their requirements and business strategies. There is a pressing need of comprehensive techniques to help them for the sustainable CSP development [5,6].

Sustainable CSP development can be formulated as a multicriteria decision-making (MCDM) problem [5]. It involves the intrinsic relations among multiple alternatives, (quantitative and qualitative) decision criteria and experts for selecting the trustworthy CSPs. Moreover, the CSP evaluation data often involves uncertain, unreliability, multi-scale and imprecise weights of quality of service (QoS) parameters, such as the availability, response time, and price [7]. The existing MCDM methods for CSP selection problems can be divided into three categories: the utility value-based methods such as the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [8], VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [9,10], and Multiplicative Multi-Objective Optimization by Ratio Analysis (MULTIMOORA) [11]; outranking methods such as the Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) [12] and ELimination and Choice Expressing the Reality (ELECTRE) [13]; and preference ordering methods such as the Analytic Hierarchical Process (AHP) [14] and the Best Worst Method (BWM) [9,15,16]. The utility value-based methods are easy to understand with a ranking set as its output, and as a result are widely applied in practice [17]. However, most of these methods have only one normalization technique in benefit and cost criteria, which would mislead the decision matrix. In addition, considering that the valuation information may be uncertain, many fuzzy MCDM methods have been proposed for CSP selection with different information representation forms [10,11,18–24] like Triangular Fuzzy Numbers (TFNs) [10], Intuitionistic Fuzzy Set (IFS) [23], Interval-Valued Intuitionistic Fuzzy Sets (IIVIFS) [18,21] and Probabilistic Linguistic Term Sets (PLTSs) [24]. However, most of these researches did not consider the reliability of the information given by decision makers.

A recently proposed MCDM method, the double normalization-based multiple aggregation (DNMA) method, [25] takes advantages of two normalization techniques and three aggregation functions to tackle quantitative and qualitative criteria in the forms of benefit, cost, and target types. Thus, it can flexibly and reliably solve MCDM problems compared with the TOPSIS, VIKOR and MULTIMOORA methods [26]. It has been integrated with PLTSs [25], rough numbers [27], and hesitant fuzzy sets [28,29] to handle the uncertain information and solve the problems of green enterprise ranking [25,27], early lung cancer screening [28], and shopping mall location selection [29]. Nevertheless, the original DNMA method cannot handle the unreliable information. Z-numbers [30] describe the fuzziness and reliability of user preferences, and thus can handle the uncertain and unreliable trust feedback data of CSPs through restriction and reliability functions under uncertainty. Therefore, the combination of DNMA and Z-number can enhance the practicability of the DNMA method in solving practical CSP selection problems. The Gini-coefficient-based weighting method can reflect the difference between any two evaluation objects [31]. Compared with other weighting methods based on the difference degrees of criteria such as the entropy-based weighting method [32], the mean-square-based weighting method [25], and the TOPSIS-based weighting method [33], the Gini-coefficient-based weighting method is not affected by the dimension of criteria unit and has the merits of better applicability and isotonicity [31].

Motivated by these analyses, this study presents a Z-number-based DNMA (Z-DNMA) method for the identification of the sustainable CSPs. The Gini-coefficient-based weight-determining method is integrated to reflect the trade-offs between QoS criteria. The main contributions of this study are highlighted as follows:

1. We introduce the DNMA method for CSP selection. The proposed model can deal with quantitative and qualitative criteria in forms of benefit, cost, and target types. It can flexibly and reliably solve the sustainable cloud service provider development problem.
2. We extend the original DNMA method to the Z-number environment and propose the Z-DNMA method to tackle quantitative and qualitative criteria in forms of benefit, cost, and target types for CSP selection. In this regard, the uncertain and unreliability decision information of decision-makers (DMs) is considered in the process of CSP selection.
3. To enhance the applicability and isotonicity and the DNMA method, we make use of the Gini-coefficient-based weighting method to replace the mean-square-based weighting method used in the original DNMA method, and extend this approach to the Z-number environment for the trade-offs between criteria after normalization.

The structure of this paper is as follows. In Section 2, some definitions and concepts are introduced. In Section 3, the Z-DNMA method is presented. In Section 4, a numerical example is presented, followed by the comparative analyses, sensitivity analysis in Section 5. Conclusions are given in the last section.

2. Preliminaries

This section primarily reviews some notions of Z-numbers and the Gini coefficient weighting method.

2.1. Generalized Triangle Fuzzy Numbers

Fuzzy set [34] was defined based on a membership function whose values are in the unit interval. A fuzzy set A is defined on a universe X as $A = \{\langle x, \mu_A(x)\rangle | x \in X\}$, where $\mu_A(x) : X \to [0,1]$ is the membership function of set A, indicating the degree of belongingness of $x \in X$ in A. A TFN $\widetilde{A}$ is defined as a triple (L, M, R) with the membership function as [34]:

$$\mu_{\widetilde{A}}(x) = \begin{cases} 0 & for \quad x < L \\ \frac{x-L}{M-L} & for \quad L \le x \le M \\ \frac{U-x}{U-M} & for \quad M \le x \le U \\ 0 & for \quad x > M \end{cases} \tag{1}$$

Let $\widetilde{A}_1 = (L_1, M_1, U_1)$ and $\widetilde{A}_2 = (L_2, M_2, U_2)$ be two TFNs, and $\lambda > 0$ be a constant number. The operations of TFNs can be performed as [27]: $\widetilde{A}_1 \oplus \widetilde{A}_2 = (L_1 + L_2, M_1 + M_2, U_1 + U_2)$, $\widetilde{A}_1 \ominus \widetilde{A}_2 = (L_1 - U_2, M_1 - M_2, U_1 - L_2)$, $\lambda\widetilde{A}_1 = (\lambda L_1, \lambda M_1, \lambda U_1)$, $\max\limits_i \widetilde{A}_i = \left(\max\limits_i L_i, \max\limits_i M_i, \max\limits_i U_i\right)$, $\min\limits_i \widetilde{A}_i = \left(\min\limits_i L_i, \min\limits_i M_i, \min\limits_i U_i\right)$. The distance between $\widetilde{A}_1$ and $\widetilde{A}_2$ was determined as [35]:

$$d\left(\widetilde{A}_1, \widetilde{A}_2\right) = \sqrt{1/3\left((L_1 - L_2)^2 + (M_1 - M_2)^2 + (U_1 - U_2)^2\right)} \tag{2}$$

The expectation value $E\left(\widetilde{A}_i\right)$ of a TFN $\widetilde{A}_i = (L_i, M_i, U_i)$ can be calculated as [35]:

$$E\left(\widetilde{A}_i\right) = \frac{L_i + 2M_i + U_i}{4} \tag{3}$$

2.2. Z-number

Zadeh [30] introduced the concept of Z-number as an ordered pair $Z = (\widetilde{A}, \widetilde{B})$ of fuzzy numbers $\widetilde{A}$ and $\widetilde{B}$, where the first component $\widetilde{A}$ is interpreted as a restriction on the values that a variable can take, and the second component $\widetilde{B}$ is a measure of reliability about the value of $\widetilde{A}$. Typically, $\widetilde{A}$ and $\widetilde{B}$ are described in a natural language, for example—low, likely. Compared with the classical fuzzy set, the Z-number takes into account the uncertainty in information generation process and the reliability of information. At present, it has been combined with many MCDM methods such as TOPSIS [36,37], VIKOR [38], Multi-Objective Optimization by Ratio Analysis (MOORA) [39], COmbinative Distance-based Assessment (CODAS) [40], PROMETHEE [41], TODIM (an acronym in Portuguese of interactive and multicriteria decision-making) [37], AHP [42], BWM [43] and Data Envelopment Analysis (DEA) [44].

For a Z-number $Z = (\widetilde{A}, \widetilde{B})$ in which $\widetilde{A} = \left\{ (x, \mu_{\widetilde{A}}) \middle| x \in [0,1] \right\}$ and $\widetilde{B} = \left\{ (x, \mu_{\widetilde{B}}) \middle| x \in [0,1] \right\}$ are two TFNs, we can convert the Z-number to an ordinary fuzzy number [45]. Firstly, the second part (reliability) can be converted into a crisp number by Equation (4):

$$\alpha = \frac{\int x\mu_B dx}{\int \mu_B dx} \tag{4}$$

where "$\int$" denotes an algebraic integration. Then, we add the weight of the second part (reliability) to the first part (restriction). The weighted Z-number is as follows:

$$\widetilde{Z}^{\alpha} = \left\{ (x, \mu_{\widetilde{A}^{\alpha}}) \middle| \mu_{\widetilde{A}^{\alpha}}(x) = \alpha \mu_{\widetilde{A}}(x), x \in [0,1] \right\} \tag{5}$$

We then convert the Z-number (weighted restriction) to the fuzzy number $\widetilde{Z}'$:

$$\widetilde{Z}' = \left\{ (x, \mu_{\widetilde{A}'}) \middle| \mu_{\widetilde{A}'}(x) = \mu_{\widetilde{A}}\left(\frac{x}{\sqrt{\alpha}} \right), x \in [0,1] \right\} \tag{6}$$

If $\widetilde{A} = (L, M, U)$ is a TFN, then $\widetilde{Z}'$ is calculated as:

$$\widetilde{Z}' = \left(\sqrt{\alpha}L, \sqrt{\alpha}M, \sqrt{\alpha}U \right) \tag{7}$$

2.3. The Gini-Coefficient-Based Weighting Method

Gini coefficient is a quantitative index to measure the difference in income distribution and has been widely used in studying impacts of inequality [46,47]. Since the Gini coefficient can reflects the data difference between different evaluation objects, Li et al. [31] proposed a method to calculate the weights of objectives based on the Gini coefficient: Suppose that G_k denotes the Gini coefficient of the k-th criterion $(k = 1, 2, \cdots, n)$, m denotes the total data of a specific criterion, y_{ki} denotes the i-th alternative' performance value under the k-th criterion, E_k denotes the expectation value of all alternatives' performance values under the k-th criterion. Then the Gini coefficient value G_k can be calculated by Equations (8) and (9) [31].

$$G_k = \sum_{i=1}^{m} \sum_{j=1}^{m} \left| y_{ki} - y_{kj} \right| / 2m^2 E_k \tag{8}$$

$$G_k = \sum_{i=1}^{m} \sum_{j=1}^{m} \left| y_{ki} - y_{kj} \right| / \left(m^2 - m \right) \tag{9}$$

In particular, when the mean value of all alternatives' performance values under a specific criterion that is not equal to 0, the Gini coefficient of the criterion is calculated by Equation (8); otherwise, the Gini coefficient of the criterion is calculated by Equation (9).

Then, we can obtain the objective weight of the k-th criterion by Equation (10).

$$w_k^G = G_k \Big/ \sum_{k=1}^{n} G_k \tag{10}$$

3. A Z-Number-Based DNMA Method

In this section, we propose a Z-number-based DNMA method with a Gini-coefficient-based weight determination method. We extend the original DNMA method to the Z-number environment. Meanwhile, we adopt the Gini-coefficient based weighting method to replace the mean-square-based weighting method used in the original DNMA method, and extend this approach to the Z-number environment for the trade-offs between criteria after normalization. The procedure of the proposed method is summarized in Figure 1.

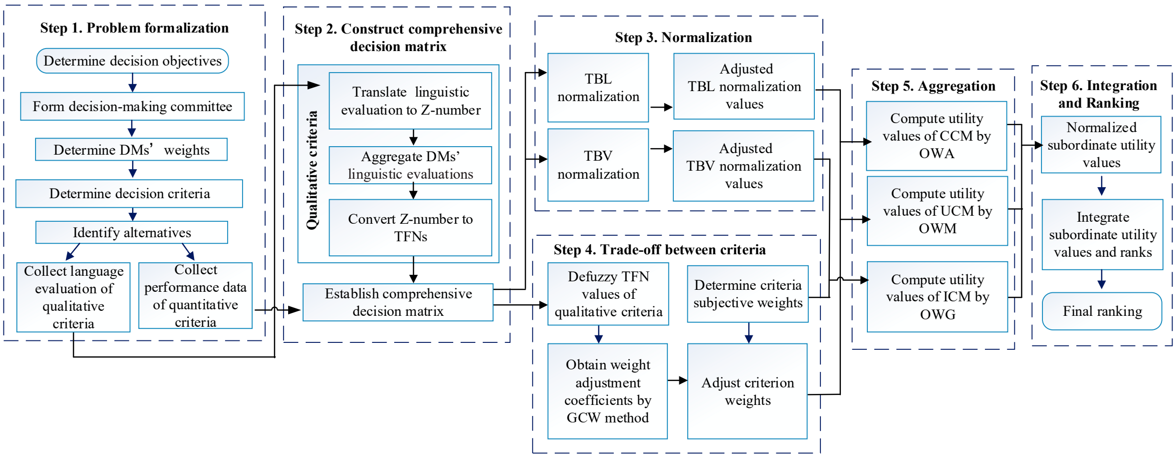

Figure 1. The procedure of the Z-number based double normalization-based multiple aggregation (Z-DNMA) method. "TBL: Target-based linear; TBV: Target-based vector; GCW: Gini coefficient-based weighting; OWA: Weighted average operator; OWM: Weighted maximum operator; OWG: Weighted geometric operator".

Step 1. (Problem formalization) Let $A = \{a_1, a_2, \cdots, a_m\}$ $(m \geq 2)$ be a set of alternatives, $C = \{c_1, c_2, \cdots, c_n\}$ $(n \geq 2)$ be a set of criteria, $D = \left\{d_1, d_2, \cdots, d_q\right\}$ $(q \geq 2)$ be a set of DMs. $W = \{w_1, w_2, \cdots, w_n\}^T$ is the weight vector of criteria, where $w_j \in [0, 1]$ and $\sum_{j=1}^{n} w_j = 1$; $\lambda = \left(\lambda_1, \lambda_2, \cdots, \lambda_q\right)^T$ is the weight vector of DMs, where $\lambda_k \geq 0$ and $\sum_{k=1}^{q} \lambda_k = 1$. Since the numerical values for quantitative criteria is easy to collect, we mainly focus on the evaluation of alternatives over qualitative criteria. For qualitative criteria $C_1 = \left\{c_1, c_2, \cdots, c_g\right\}$, we suppose their values of alternatives are evaluated by the $k-$th DM and expressed as linguistic expressions $s_{ij}^{(k)}$, for $i = 1, 2, \cdots, m, j = 1, 2, \cdots, g$, $k = 1, 2, \cdots, q$. For quantitative criteria $C_2 = \left\{c_{g+1}, c_{g+2}, \cdots, c_n\right\}$, we suppose the values of alternatives are expressed as numerical numbers x_{ij}, for $i = 1, 2, \cdots, m$, $j = g + 1, g + 2, \cdots, n$.

Step 2. (Constructing comprehensive decision matrix)

Step 2.1. Translate each DM's linguistic evaluation $s_{ij}^{(k)}$ to Z-number, and then the decision matrix of the $k-$th DM can be expressed as:

$$X^{(k)} = \left[z_{ij}^{(k)}\right]_{m\times g} = \left[\left(A_{ij}^{(k)}, B_{ij}^{(k)}\right)\right]_{m\times g}, \text{ for } k = 1, 2, \cdots, q,$$

where $z_{ij}^{(k)}$ denotes the Z-fuzzy performance evaluation value of the $i-$th alternative on the $j-$th criterion from $k-$th DM.

Step 2.2. According to the weights of DMs, $\lambda = \left(\lambda_1, \lambda_2, \cdots, \lambda_q\right)^T$, aggregate DMs' linguistic evaluations into collective ones based on the weighted arithmetic aggregation operator as:

$$\overline{X} = \left[\overline{z}_{ij}\right]_{m\times g} = \left[\left(\overline{A}_{ij}, \overline{B}_{ij}\right)\right]_{m\times g} = \left[\left(\sum_{k=1}^{q} \lambda_k A_{ij}^k, \sum_{k=1}^{q} \lambda_k B_{ij}^k,\right)\right]_{m\times g} \tag{11}$$

Step 2.3. Convert Z-fuzzy performance values to TFNs $\overline{z}'_{ij}$ by Equations (4) and (7), where $\widetilde{z}'_{ij} = \left(\overline{z}'_{ijL}, \overline{z}'_{ijM}, \overline{z}'_{ijU}\right)$, for $i = 1, 2, \cdots, m$, $j = 1, 2, \cdots, g$.

Step 2.4. Establish the comprehensive decision matrix X', which is composed by the calculated TFNs and numerical numbers, shown as:

$$X' = \begin{bmatrix} \overline{z}'_{11} & \cdots & \overline{z}'_{1g} & x_{1g+1} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \overline{z}'_{i1} & \cdots & \overline{z}'_{ig} & x_{1g+1} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \overline{z}'_{m1} & \cdots & \overline{z}'_{mg} & x_{mg+1} & \cdots & x_{mn} \end{bmatrix} \tag{12}$$

Step 3. (Normalization) Distinguish the criteria into benefit, cost, and target forms. Based on the decision matrix X', we calculate the target-based linear normalization values by Equation (13) based on the distance measure given as Equation (2) and the target-based vector normalization values by Equation (14) based on the expectation function given as Equation (3).

$$\widetilde{x}_{ij}^{1N} = 1 - \frac{d_{ij}}{\max\limits_i d_{ij}}, \text{ where } d_{ij} = \begin{cases} d\left(\overline{z}'_{ij}, \widetilde{z}'_j\right), & \text{for } j = 1, 2, \cdots, g \\ \left|x_{ij} - r_j\right|, & \text{for } j = g+1, g+2, \cdots, n \end{cases} \tag{13}$$

$$\widetilde{x}_{ij}^{2N} = \begin{cases} 1 - \dfrac{\left|E\left(\overline{z}'_{ij}\right) - E\left(\widetilde{z}'_j\right)\right|}{\sqrt{\sum\limits_{i=1}^{m}\left(E\left(\overline{z}'_{ij}\right)\right)^2 + \left(E\left(\widetilde{z}'_j\right)\right)^2}} & if\ j = 1, 2, \cdots, g \\ 1 - \dfrac{\left|x_{ij} - r_j\right|}{\sqrt{\sum\limits_{i=1}^{m}\left(x_{ij}\right)^2 + \left(r_j\right)^2}} & if\ j = g+1, g+2, \cdots, n \end{cases} \tag{14}$$

where $\widetilde{z}'_{ij}$ is the target value on qualitative criteria c_j $(j = 1, 2, \cdots, g)$, and r_j is the target value on quantitative criteria $(j = g+1, g+2, \cdots, n)$. Especially, if the jth criterion is a qualitative criterion, then,

$$\widetilde{z}'_j = \begin{cases} \left(\max\limits_i \overline{z}'_{ijL}, \max\limits_i \overline{z}'_{ijM}, \max\limits_i \overline{z}'_{ijU}\right), & \text{for the benefit criterion} \\ \left(\min\limits_i \overline{z}'_{ijL}, \min\limits_i \overline{z}'_{ijM}, \min\limits_i \overline{z}'_{ijU}\right), & \text{for the cos t criterion} \end{cases} \tag{15}$$

If the jth criteria is a quantitative criterion, then,

$$r_j = \begin{cases} \max\limits_i x_{ij}, & \text{for the benefit criterion} \\ \min\limits_i x_{ij}, & \text{for the cos t criterion} \end{cases} \tag{16}$$

Afterwards, the target-based liner and vector normalization values are adjusted by Equation (17) to make the maximum entry as 1 under each criterion.

$$\begin{cases} \hat{x}_{ij}^{1N} = \widetilde{x}_{ij}^{1N} / \max\limits_i \widetilde{x}_{ij}^{1N} \\ \hat{x}_{ij}^{2N} = \widetilde{x}_{ij}^{2N} / \max\limits_i \widetilde{x}_{ij}^{2N} \end{cases} \tag{17}$$

Step 4. (Trade-offs between criteria) In the original DNMA method, Liao & Wu [14] adjusted the criteria weights based on the mean-squared-based weighting method. In this study, we make use of the Gini-coefficient-based weighting method to replace it and extend this approach to the Z-number environment. Firstly, we defuzzify the TFNs of qualitative criteria in the comprehensive decision matrix X' to expectation values $E\left(\overline{z}'_{ij}\right)$ by Equation (3) and obtain the weight adjustment coefficients of the criteria by Equations (8)–(10). Then, the criteria weights are adjusted by

$$\widetilde{w}_j = \sqrt{w_j^G \cdot w_j} \Big/ \sum_{j=1}^{n} \sqrt{w_j^G \cdot w_j}, \text{ for } j = 1, 2, \cdots, n \tag{18}$$

Step 5. (Aggregation) Compute the subordinate utility values of each alternative, $u_h(a_i), h = 1, 2, 3;$ $i = 1, 2, \cdots, m$, based on the complete compensatory model (CCM), un-compensatory model (UCM), and incomplete compensatory model (ICM) by Equations (19)–(21), respectively. Then, determine the subordinate ranks $r_h(a_i), h = 1, 2, 3; i = 1, 2, \cdots, m$. Go to the next step.

$$u_1(a_i) = \sum_{j=1}^{n} \widetilde{w}_j \hat{x}_{ij}^{1N} \tag{19}$$

$$u_2(a_i) = \max_{j=1} \widetilde{w}_j \left(1 - \hat{x}_{ij}^{1N}\right) \tag{20}$$

$$u_3(a_i) = \prod_j \left(\hat{x}_{ij}^{2N}\right)^{w_j} \tag{21}$$

It is noted that Equations (19) and (20) are based on the adjusted weight $\widetilde{w}_j$ of criterion c_j, while Equation (21) is based on the original weight w_j of c_j.

Step 6. (Integration and Ranking) Calculate the normalized subordinate utility values $u_y^N(a_i)$, $y = 1, 2, 3; i = 1, 2, \cdots, m$, by Equation (22).

$$u_Y^N(a_i) = \frac{u_Y(a_i)}{\sqrt{\sum_{i=1}^{m} (u_Y(a_i))^2}}, Y = 1, 2, 3 \tag{22}$$

Determine the weights of the CCM, UCM and ICM. Then, we can integrate the normalized subordinate utility values and subordinate ranks by Equation (23), and obtain the collective utility value of each alternative DN_i, $i = 1, 2, \cdots, m$:

$$
\begin{aligned}
DN_i \quad &= w'_1 \sqrt{\varphi\Big(u_1^N(a_i)/\max_i u_1^N(a_i)\Big)^2 + (1-\varphi)\Big(\tfrac{m-r_1(a_i)+1}{m}\Big)^2} \\
&-w'_2 \sqrt{\varphi\Big(u_2^N(a_i)/\max_i u_2^N(a_i)\Big)^2 + (1-\varphi)\Big(\tfrac{r_2(a_i)}{m}\Big)^2} \\
&+w'_3 \sqrt{\varphi\Big(u_3^N(a_i)/\max_i u_3^N(a_i)\Big)^2 + (1-\varphi)\Big(\tfrac{m-r_3(a_i)+1}{m}\Big)^2}
\end{aligned} \tag{23}
$$

where $r_1(a_i)$ and $r_3(a_i)$ are the ranks of alternative a_i and determined in descending order of $u_1(a_i)$ and $u_3(a_i)$, respectively, $r_2(a_i)$ is the rank of alternative a_i and determined by the ascending order of $u_2(a_i)$, $\varphi(\varphi \in [0,1])$ is the relative importance of the subordinate ranks and subordinate utility values. w'_1, w'_2, w'_3 denote the weights of CCM, UCM and ICM, satisfying $w'_i \in [0,1]$ and $\sum_{i=1}^{3} w'_i = 1$.

Lastly, we can determine the final ranking according to the descending order of DN_i and end the algorithm.

4. Case Study on CSP Ranking with the Z-DNMA Method

In this section, the Z-DNMA method is illustrated with a numerical example related to the CSP selection problem.

Assume that a company plans to consume a cloud service request and thus needs to select the most suitable cloud services. After multiple rounds of anonymous discussions and summarizing, the five evaluation criteria are selected from the QoS attributes and based on the Delphi method which involved X IT experts in the field of cloud computing. The determined criteria are as follows:

Cost c_1 (qualitative, target): The cost involved in using a cloud service, including computer costs, storage costs, transfer costs, and application costs.

Reliability c_2 (qualitative, max): The reliability in a cloud refers to how a cloud service operates without failure under a set of operating conditions for a specific period of time.

Availability c_3 (qualitative, max): Whether a cloud service exists and is available instantly.

Response Time (minutes) c_4 (quantitative, min): It represents the time elapsed to send a request by the client and receiving an answer provided by the cloud service.

Throughput (hits/sec) c_5 (quantitative, max): It represents the total number of invocations for a given time period. The unit of measure is invocations per second for a given cloud service.

Assume that there are four CSPs $A = \{a_1, a_2, a_3, a_4\}$ left after a preliminary screen. Three DMs $d_q(q = 1,2,3)$ are invited to assess the performances of CSPs with respect to each qualitative criterion, and the three DMs have the same importance, i.e., $\lambda_1 = \lambda_2 = \lambda_3 = 1/3$. The qualitative attributes are assessed based on questionnaire using the scales given in Tables 1 and 2. The qualitative evaluation results are shown in Table 3. For quantitative attributes c_4 and c_5 (i.e., response time and throughput), the performances of the alternatives are obtained from the service level agreements of the CSPs, shown as (118, 75, 71, 103) and (25, 17, 11, 16), respectively.

Table 1. Transformation rules of linguistic variables of restriction.

Scale		**Membership Function**
c_1	c_2 c_3	
Very High (VH)	Very Low (VL)	(0,0,1)
High (H)	Low (L)	(0,1,3)
Medium High (MH)	Medium Low (ML)	(1,3,5)
Medium (M)	Medium (M)	(3,5,7)
Medium Low (ML)	Medium High (MH)	(5,7,9)
Low (L)	High (H)	(7,9,10)
Very Low (VL)	Very High (VH)	(9,10,10)

Table 2. Transformation rules of linguistic variables of reliabilities.

Scale	Membership Function
Strongly Unlikely (SU)	(0,0,0.1)
Unlikely (U)	(0,0.1,0.3)
Somewhat Unlikely (SWU)	(0.1,0.3,0.5)
Neutral (N)	(0.3,0.5,0.7)
Somewhat Likely (SWL)	(0.5,0.7,0.9)
Likely (L)	(0.7,0.9,1)
Strongly Likely (SL)	(0.9,1,1)

Table 3. The evaluation information given by decision-makers (DMs).

DMs	CSPs	c_1	c_2	c_3
DM1	a_1	(ML, L)	(MH, L)	(ML, N)
	a_2	(MH, SL)	(MH, L)	(H, SWU)
	a_3	(H, N)	(H, L)	(H, N)
	a_4	(VL, SWL)	(MH, SWL)	(ML, L)
DM2	a_1	(M, L)	(H, SL)	(ML, N)
	a_2	(MH, L)	(H, L)	(H, N)
	a_3	(MH, N)	(MH, L)	(H, SWL)
	a_4	(VL, SWL)	(MH, SWL)	(ML, L)
DM3	a_1	(ML, L)	(H, SL)	(M, SWU)
	a_2	(MH, L)	(MH, L)	(H, SWL)
	a_3	(H, N)	(H, L)	(H, SWL)
	a_4	(VL, N)	(M, L)	(ML, L)

Below we use the Z-DNMA method presented in Section 3 to solve this problem. Since Step 1 is given above, we start the calculation process from Step 2.

Step 2. Convert each DM's linguistic evaluations to Z-numbers based on Tables 1 and 2.

The converted results are shown in Table 4. Then, aggregate DMs' linguistic evaluations into collective ones by Equation (11) The aggregated decision matrix is shown in Table 5. Furthermore, we convert Z-fuzzy performance values to TFNs by Equations (4) and (7). The comprehensive decision matrix X', which is combined with the performance values of quantitative criteria, is obtained as follows:

$$X' = \begin{bmatrix} (4.034,\ 5.896,\ 7.758) & (6.118,\ 8.051,\ 9.339) & (1.097,\ 2.414,\ 3.73) & 118 & 25 \\ (0.949,\ 2.846,\ 4.743) & (5.275,\ 7.137,\ 8.689) & (4.95,\ 6.364,\ 7.071) & 75 & 17 \\ (0.236,\ 1.179,\ 2.593) & (5.896,\ 7.758,\ 8.999) & (5.571,\ 7.162,\ 7.958) & 71 & 11 \\ (7.162,\ 7.958,\ 7.958) & (3.767,\ 5.505,\ 7.244) & (0.931,\ 2.793,\ 4.655) & 103 & 16 \end{bmatrix} \quad (24)$$

Table 4. The decision matrix described by Z-numbers.

DMs	CSPs	c_1		c_2		c_3	
		Restriction	**Reliability**	**Restriction**	**Reliability**	**Restriction**	**Reliability**
DM1	a_1	(5,7,9)	(0.7,0.9,1)	(5,7,9)	(0.7,0.9,1)	(1,3,5)	(0.3,0.5,0.7)
	a_2	(1,3,5)	(0.9,1,1)	(5,7,9)	(0.7,0.9,1)	(7,9,10)	(0.1,0.3,0.5)
	a_3	(0,1,3)	(0.3,0.5,0.7)	(7,9,10)	(0.7,0.9,1)	(7,9,10)	(0.3,0.5,0.7)
	a_4	(9,10,10)	(0.5,0.7,0.9)	(5,7,9)	(0.5,0.7,0.9)	(1,3,5)	(0.7,0.9,1)
DM2	a_1	(3,5,7)	(0.7,0.9,1)	(7,9,10)	(0.9,1,1)	(1,3,5)	(0.3,0.5,0.7)
	a_2	(1,3,5)	(0.7,0.9,1)	(7,9,10)	(0.7,0.9,1)	(7,9,10)	(0.3,0.5,0.7)
	a_3	(1,3,5)	(0.3,0.5,0.7)	(5,7,9)	(0.7,0.9,1)	(7,9,10)	(0.5,0.7,0.9)
	a_4	(9,10,10)	(0.5,0.7,0.9)	(5,7,9)	(0.5,0.7,0.9)	(1,3,5)	(0.7,0.9,1)
DM3	a_1	(5,7,9)	(0.7,0.9,1)	(7,9,10)	(0.9,1,1)	(3,5,7)	(0.1,0.3,0.5)
	a_2	(1,3,5)	(0.7,0.9,1)	(5,7,9)	(0.7,0.9,1)	(7,9,10)	(0.5,0.7,0.9)
	a_3	(0,1,3)	(0.3,0.5,0.7)	(7,9,10)	(0.7,0.9,1)	(7,9,10)	(0.5,0.7,0.9)
	a_4	(9,10,10)	(0.3,0.5,0.7)	(3,5,7)	(0.7,0.9,1)	(1,3,5)	(0.7,0.9,1)

Table 5. The aggregated decision matrix.

CSPs	c_1	c_2	c_3
a_1	((4.333, 6.333, 8.333), (0.7, 0.9, 1))	((6.333, 8.333, 9.667), (0.833, 0.967, 1))	((1.667, 3.667, 5.667), (0.233, 0.433, 0.633))
a_2	((1, 3, 5), (0.767, 0.933, 1))	((5.667, 7.667, 9.333), (0.7, 0.9, 1))	((7, 9, 10), (0.3, 0.5, 0.7))
a_3	((0.333, 1.667, 3.667), (0.3, 0.5, 0.7))	((6.333, 8.333, 9.667), (0.7, 0.9, 1))	((7, 9, 10), (0.433, 0.633, 0.833))
a_4	((9, 10, 10), (0.433, 0.633, 0.833))	((4.333, 6.333, 8.333), (0.567, 0.767, 0.933))	((1, 3, 5), (0.7, 0.9, 1))

Step 3. Suppose that the target value of c_1 is "Medium", i.e., (3, 5, 7). In addition, the target values of c_2, c_3, c_4, c_5 can be computed by Equations (15) and (16). We can obtain the target value of each criterion as: $\widetilde{z}'_1$ = (3, 5, 7), $\widetilde{z}'_2$ = (6.118, 8.051, 9.339), $\widetilde{z}'_3$ = (5.571, 7.162, 7.958), r_4 = 71, r_5 = 25. Then, the target-based linear normalization values can be computed by Equations (13) and (2), while the target-based vector normalization values can be computed by Equations (14) and (3). The results are shown in Tables 6 and 7, respectively.

Table 6. The target-based linear normalized values.

CSPs	c_1	c_2	c_3	c_4	c_5
a_1	0.758	1.000	0.000	0.000	1.000
a_2	0.422	0.654	0.827	0.915	0.429
a_3	0.000	0.877	1.000	1.000	0.000
a_4	0.195	0.000	0.077	0.319	0.357

Table 7. The target-based vector normalized values.

CSPs	c_1	c_2	c_3	c_4	c_5
a_1	0.921	1.000	0.627	0.766	1.000
a_2	0.811	0.949	0.936	0.980	0.817
a_3	0.675	0.982	1.000	1.000	0.680
a_4	0.758	0.853	0.658	0.840	0.794

From Tables 6 and 7, we can find that only the maximum target-based linear normalization value and the maximum target-based vector normalization value under criterion c_1 are smaller than 1. Therefore, we only adjust the normalized values under this criterion c_1 by Equation (17).

Step 4. Defuzzify the TFN values of qualitative criteria, which are listed in the comprehensive decision matrix X' to crisp values by Equation (3). The crisp performance matrix is shown as follows:

$$\begin{bmatrix} 5.896 & 7.89 & 2.414 & 118 & 25 \\ 2.846 & 7.06 & 6.187 & 75 & 17 \\ 1.296 & 7.603 & 6.963 & 71 & 11 \\ 7.759 & 5.505 & 2.793 & 103 & 16 \end{bmatrix} \tag{25}$$

Then, we can calculate the Gini coefficient of each criterion by Equation (8): $G_1 = 0.315$, $G_2 = 0.069$, $G_3 = 0.232$, $G_4 = 0.115$, $G_5 = 0.156$. In addition, we obtain the weight adjustment coefficients of the criteria by Equation (10): $w_1^G = 0.355$, $w_2^G = 0.077$, $w_3^G = 0.262$,$w_4^G = 0.130$, $w_5^G = 0.176$. Suppose that the DMs assign the subjective weights of criteria as: $w_1 = 0.094$, $w_2 = 0.445$, $w_3 = 0.379$, $w_4 = 0.045$, $w_5 = 0.037$. By Equation (18), we obtain the adjusted weights of the criteria as $\widetilde{w}_1 = 0.217$, $\widetilde{w}_2 = 0.220$, $\widetilde{w}_3 = 0.375$, $\widetilde{w}_4 = 0.091$, $\widetilde{w}_5 = 0.096$. Step 5. We calculate utility values of CCM, UCM, and ICM by Equations (19), (20) and (21), respectively. The results are shown in Table 8.

Table 8. The utility values of alternatives derived by the Z-DNMA method.

CSPs	CCM		UCM		ICM	
	$u_1(a_i)$	$r_1(a_i)$	$u_2(a_i)$	$r_2(a_i)$	$u_3(a_i)$	$r_3(a_i)$
a_1	0.534	3	0.375	4	0.828	3
a_2	0.700	1	0.096	1	0.934	2
a_3	0.659	2	0.217	2	0.950	1
a_4	0.148	4	0.346	3	0.768	4

Step 6. Normalize the utility values by Equation (22). Then, suppose $\varphi = 0.5$, $w'_1 = 0.3$, $w'_2 = 0.3$, $w'_3 = 0.4$. The subordinate normalized utility values and the subordinate ranks are integrated by Equation (23). We can obtain the final utility values as $DN_1 = 0.178$, $DN_2 = 0.574$, $DN_3 = 0.493$, $DN_4 = 0.057$. Therefore, the final ranking of alternatives is $a_2 > a_3 > a_1 > a_4$.

From the above example, we can find that the proposed method has the following merits: (1) It can flexibly handle uncertain and unreliable trust-feedback data of the CSPs. It is not only a comprehensive reflection of DMs' judgments but also conforms to the expression habits of DMs; (2) It can deal with the decision-making problems which include quantitative and qualitative criteria in forms of benefit, cost, and target types. It can solve the sustainable cloud service provider development problem flexibly and reliably.

5. Discussion

In this section, we compare the results of the proposed method with the results obtained by the original DNMA method and other existing methods including the Z-TOPSIS method and Z-VIKOR method. Then, we perform sensitive analysis to validate the robustness of the proposed method.

5.1. Comparative Analysis

5.1.1. Solving the Case by the Original DNMA Method

In the original DNMA method, Liao & Wu [25] adjust the criteria weights by the mean-squared-based weighting method. In this subsection, we recalculate the results by the original DNMA method.

By the mean-squared-based weighting method, the weight adjustment coefficients are {0.297, 0.106, 0.263, 0.151, 0.183}. Then, we can obtain the adjusted weights as {0.193, 0.252, 0.365, 0.095, 0.095} by Equation (18). Using Equations (19)–(23), we can get $DN_1 = 0.179$, $DN_2 = 0.576$, $DN_3 = 0.506$, $DN_4 = 0.055$. Therefore, the final ranking is $a_2 > a_3 > a_1 > a_4$. We can find that the result calculated by the original DNMA method is consistent with that deduced by our proposed method.

5.1.2. Solving the Case by the Z-TOPSIS Method

Next, we apply the Z-TOPSIS to solve this case. The TOPSIS method selects the optimal alternative that has the shortest distance to the positive ideal solution A^+ and the furthest distance from the negative ideal solution A^-. The classical TOPSIS normalized the decision matrix by vector normalization. Yaakob and Gegov [36] extended the classical TOPSIS method into the Z-numbers environment and implemented it in the stock selection problem, but that method could not support the MCDM with target criteria. We extend the TOPSIS method into the Z-fuzzy environment by combining it with the target-based vector normalization method (i.e., Equation (14)).

First, we use the target-based vector normalization method given as Equation (14) to normalize the decision matrix X' and obtain $\widetilde{x}_{ij}^{2N} (i = 1, 2, 3, 4; j = 1, 2, 3, 4, 5)$ as shown in Table 7. Then, we use

Equation (17) to adjust $\widetilde{x}_{ij}^{2N}$ to $\hat{x}_{ij}^{2N}$. Furthermore, the Euclidean distance between positive solution (s_i^+) and negative ideal solution (s_i^-) can be calculated by

$$s_i^+ = \sqrt{\sum_{j=1}^{n} \widetilde{w}_j \left(\hat{x}_{ij}^{2N} - \left(\hat{x}_{ij}^{2N}\right)^+\right)^2},\ s_i^- = \sqrt{\sum_{j=1}^{n} \widetilde{w}_j \left(\hat{x}_{ij}^{2N} - \left(\hat{x}_{ij}^{2N}\right)^-\right)^2} \tag{26}$$

where $\left(\hat{x}_{ij}^{2N}\right)^+ = \max_i\left(\hat{x}_{ij}^{2N}\right)$, $\left(\hat{x}_{ij}^{2N}\right)^- = \min_i\left(\hat{x}_{ij}^{2N}\right)$ and $\widetilde{w}_j$ is the adjusted criterion weight.

Calculate the relative closeness of each alternative to the ideal solution by Equation (27) and rank the alternatives according to descending order of RC_i.

$$RC_i = s_i^- / \left(s_i^- + s_i^+\right) \tag{27}$$

The calculation results are shown in Table 9. According to the calculation results, the final ranking of the alternatives is $a_2 > a_3 > a_1 > a_4$, which is consistent with the result derived by the Z-DNMA method.

Table 9. The calculation results with the Z-TOPSIS method.

CSPs	s_i^+	s_i^-	RC_i	Rank
a_1	0.239	0.174	0.421	3
a_2	0.092	0.220	0.705	1
a_3	0.160	0.247	0.607	2
a_4	0.249	0.062	0.200	4

5.1.3. Solving the Case by the Z-VIKOR Method

The major advantage of the VIKOR method is that it can trade off the maximum group utility of the "majority" and the minimum individual regret of the "opponent". It normalizes the decision matrix by linear normalization. Here, we extend the VIKOR method into the Z-fuzzy environment by combining it with the target-based linear normalization method (i.e., Equation (13)).

First, we use the target-based linear normalization method given as Equation (13) to normalize the decision matrix X', and obtain $\widetilde{x}_{ij}^{1N}$ $(i = 1,2,3,4; j = 1,2,3,4,5)$ shown in Table 6. Then, we use Equation (17) to adjust $\widetilde{x}_{ij}^{1N}$ to $\hat{x}_{ij}^{1N}$. Additionally, we use $S_i = \sum_{j=1}^{n} \widetilde{w}_j \cdot \hat{x}_{ij}^{1N}$ and $R_i = \max_j\left(\widetilde{w}_j \cdot \left(1 - \hat{x}_{ij}^{1N}\right)\right)$ to calculate the "group utility" value S_i of each alternative and the "individual regret" value R_i of the "opponent" of each alternative, respectively.

We then calculate the compromise value Q_i of each alternative by

$$Q_i = \rho(S_i - S^-)/\left(S^+ - S_i\right) + (1 - \rho)\left(R^+ - R_i\right)/\left(R^+ - R^-\right) \tag{28}$$

where $S^+ = \max_i S_i$, $S^- = \min_i S_i$, $R^+ = \min_i R_i$, $R^- = \max_i R_i$. In addition, ρ is the weight of the strategy of "the majority of criteria" (or "the maximum group utility"). Here, we set different values for ρ (ρ = 0.25, 0.5, 0.75).

Finally, we rank the alternatives and sort the values S_i, R_i, and Q_i in descending order. The results are listed in Table 10. From Table 10, we can find that the results obtained by the Z-VIKOR method are also consistent with the results derived by the Z-DNMA method.

Table 10. The ranking of alternatives by R, S and Q values.

CSPs	S_i	R_i	$\rho = 0.25$		$\rho = 0.5$		$\rho = 0.75$	
			Q_i	Rank	Q_i	Rank	Q_i	Rank
a_1	**0.534**	0.375	0.175	3	0.350	3	0.524	3
a_2	0.700	0.096	1.000	1	1.000	1	1.000	1
a_3	0.659	0.217	0.656	2	0.746	2	0.836	2
a_4	0.148	0.346	0.078	4	0.052	4	0.026	4

5.2. Sensitivity Analysis

To test the robustness of the ranking result, four sensitivity tests are carried out in this subsection.

First, we adopt a weight replacement strategy for sensitivity test. Figure 2 contains the ten different tests to exchange the subjective weights of criteria and demonstrates the corresponding ranks of alternatives. For example, c_2-c_5 denote that the subjective weights of criteria c_2 and criteria c_5 have been interchanged. From Figure 2, it is clear that a_2 has the highest rank in seven out of ten weighted calculation experiments, and a_4 has the lowest rank in all experiments. This suggests that the optimal and worst CSPs have not altered in most cases, which illustrates the stability of the ranking results.

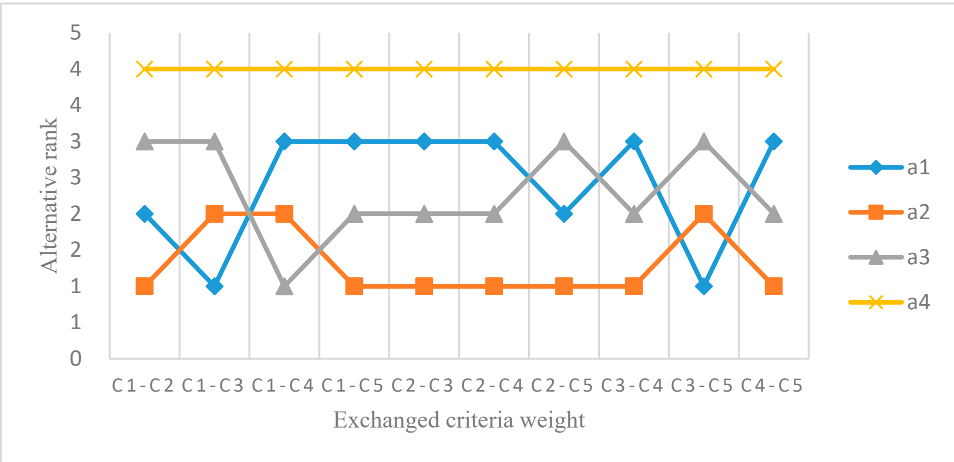

Figure 2. The results of sensitivity analysis by weight replacement.

Second, according to Equation (23) (in Step 6) of the Z-DNMA method, the collective utility value DN_i of each alternative largely depends on the proportion of φ for the relative importance of the subordinate ranks and subordinate utility values. The parameter φ is the adjustment parameter that varies in [0, 1] and is set as 0.5 in this study. To validate the impact of φ on the CSP ranking, a sensitivity test is performed on the identical application in Section 4. with φ = (0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1). The ranking results of each alternative are obtained in Table 11.

Table 11. The orders of alternatives with different φ.

CSPs	$\varphi = 0$	$\varphi = 0.1$	$\varphi = 0.2$	$\varphi = 0.3$	$\varphi = 0.4$	$\varphi = 0.5$	$\varphi = 0.6$	$\varphi = 0.7$	$\varphi = 0.8$	$\varphi = 0.9$	$\varphi = 1$
a_1	3	3	3	3	3	3	3	3	3	3	3
a_2	1	1	1	1	1	1	1	1	1	1	1
a_3	2	2	2	2	2	2	2	2	2	2	2
a_4	4	4	4	4	4	4	4	4	4	4	4

From Table 11, we can see that for the change of φ, 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 this sensitivity analysis.

Third, according to Equation (23) (in Step 6) of the Z-DNMA method, the parameter w'_1, w'_2, w'_3 denote the weights of CCM, UCM and ICM, satisfying $w'_i \in [0,1]$ and $\sum_{i=1}^{3} w'_i = 1$. The values of w'_1, w'_2, and w'_3 can be assigned different values depends on DMs' risk preferences. In this case study, we set DMs' risk preferences vector as $W' = (0.3,\ 0.3,\ 0.4)$ for demonstration. To validate the impact of W' on the CSP ranking, a sensitivity test is performed with W'_1 = (1, 0, 0), W'_2 = (0.4, 0.3, 0.3), W'_3 = (0, 1, 0), W'_4 = (0.3, 0.4, 0.3), W'_5 = (1/3, 1/3, 1/3), W'_6 = (0, 0, 1). The ranking results of each alternative are obtained in Table 12.

Table 12. The orders of alternatives with different DMs' risk preferences vector.

CSPs	W'_1	W'_2	W'_3	W'_4	W'_5	W'_6	W'
a_1	3	3	4	3	3	3	3
a_2	1	1	1	1	1	2	1
a_3	2	2	2	2	2	1	2
a_4	4	4	3	4	4	4	4

From Table 12, it can be clearly seen that under the change of the weights of DMs' risk preferences, the rank order of the alternatives is without obvious change and the final ranking is reliable and robust.

Last, we add an alternative a_5 to test the stability of the results. The linguistic evaluation values of each qualitative criteria of a_5 are shown in Table 13. The performance values of quantitative criteria are 90 min, and 10 hits/sec, respectively.

Table 13. The evaluation matrix DMs for a_5.

DMs	c_1	c_2	c_3
DM1	(MH, L)	(MH, SWL)	(M, N)
DM2	(MH, L)	(MH, L)	(MH, N)
DM3	(M, SWL)	(MH, L)	(M, SWL)

According to the calculation steps of Z-DNMA, we can obtain DN_1 = 0.183, DN_2 = 0.589, DN_3 = 0.512, DN_4 = 0.042, DN_5 = 0.284. Therefore, the final ranking is $a_2 \succ a_3 \succ a_5 \succ a_1 \succ a_4$. The results show that when a new alternative is added, the original ranking remains stable.

According to the above four sensitivity analysis, it can be concluded that a_4 is the trustworthy CSP since it has the minimal fluctuations in all the sensitivity test and the proposed method in this paper is robust and stable.

6. Conclusions

In this study, we introduced the original DNMA method to tackle quantitative and qualitative decision criteria in the forms of benefit, cost, and target types for the CSP development problem. We extended the DNMA method to Z-number environment and proposed the Z-DNMA method. In this regard, the uncertain and unreliability decision-making information of decision-makers was considered. We made use of the Gini coefficient-based weighting method to replace the mean-square-based weighting method used in the original DNMA method, and extended this approach to the Z-number environment for the trade-offs between criteria after normalization to enhance the applicability and isotonicity of the DNMA method. Based on the established decision-making method, a case study was conducted. Sensitivity analysis and comparative analysis were provided to test the stability and applicability of the proposed method.

Due to the cloud services as well as CSPs increasing rapidly with different functionalities and dynamic user requirements, the sustainable CSP development becomes an MCDM problem and remains a challenging research area in the field of cloud computing. The presented Z-DNMA method with the Gini-coefficient-based weight determination approach is utterly useful for customers to trickle quantitative and qualitative criteria in forms of benefit, cost, and target types for the sustainable CSP development, while considering the uncertain and unreliability decision-making information of DMs. First, based on linguistic Z-numbers, the proposed model can flexibly handle uncertain and unreliability trust feedback data of the CSPs. It is not only a comprehensive reflection of DMs' judgments, but also conforms to expression habits of DMs. Second, by the DNMA method, the proposed model can deal with such scenarios, which include quantitative and qualitative criteria in forms of benefit, cost, and target types. It can flexibly, reliably, and simply to solve MEMCDM for the sustainable cloud service provider development problem. Furthermore, by integrating the Gini-coefficient-based weighting method to replace the mean-square-based weighting method used in the original DNMA method and extending this approach to the Z-number environment for the trade-offs between criteria after normalization, the applicability and isotonicity of the DNMA method have been enhanced. Therefore, this study provided practical and theoretical guidance for sustainable CSP development to solve uncertainty and unreliable, multi-scale QoS assessment data to helps both researchers and practitioners for analyzing more fruitful approaches for CSP selection.

A limitation is that this paper uses a numerical example to show the effectiveness of the proposed method. In the future, we will employ the proposed method to dispose of the CSP selection problem under realistic data and cases. In addition, another limitation is that we assume that all criteria are independent in this study. We plan to develop a novel aggregation operator to aggregate the interactive criteria for better adapting to real decision-making problems.

Author Contributions: H.L. (Han Lai) and H.L. (Huchang Liao) proposed the original idea and conceived the study. H.L. (Han Lai), H.L. (Huchang Liao), J.Š., and A.B., were responsible for developing the method, collecting and analyzing the data. The paper was written by H.L. (Han Lai) and H.L. (Huchang Liao), and finally checked and revised by J.Š., A.B., and F.A.F.F. and A.A.-B. All authors have read and agreed to the published version of the manuscript.

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