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Demand Side Management Performance Evaluation for Commercial Enterprises

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Abstract: Demand Side Management in power systems plays an important role in ensuring a reliable power supply and protecting the environment. Demand Side Management in the commercial sector is vital for sustainable development during China's industrial restructuring. A hybrid multi-criteria decision making framework for evaluating Demand Side Management performance of commercial enterprises is proposed from a sustainability perspective. A fuzzy Analytic Hierarchy Process is employed to determine the weights of the criteria and a fuzzy technique for order preference by similarity to an ideal solution is applied to rank Demand Side Management performance. An evaluation index system is built, containing economic, social, environmental and technical criteria associated with 15 sub-criteria. Four groups of expert panels from government departments, research institutions, electricity utilities and commercial enterprises gave judgments on criteria weights and criteria performances for alternatives. The effectiveness of the proposed hybrid framework was demonstrated through a case study in Beijing, in which Demand Side Management performances of four alternatives were ranked. Sensitivity analysis results indicate that the hybrid framework is robust.

Keywords: DSM performance evaluation; commercial enterprise; fuzzy set theory; sensitivity analysis

1. Introduction

As the largest energy consumer and CO_2 emitter in the world, China suffers from an increasing plague of pollutant emissions, smog and water quality degradation [1,2]. Considering the imbalanced economic and social development nationwide, insufficient power supplies still exist in some regions including North China, the Yangtze River Delta and the Pearl River Delta during summers [3]. Demand Side Management (DSM) is conducted to improve the terminal users' power consumption pattern, optimize power resources distribution and promote equipment utilization. Through DSM we can balance electrical power load, overcome electrical shortage, improve terminal energy efficiency, promote clean energy power absorption, reduce greenhouse gas emissions and improve sustainable development of the electric power industry [4,5]. DSM is an important mission to meet the target of an electricity market reform in 2015 [6].

Following China's industrial structure adjustment policy, the commercial sector, generally referring to the service industry or the tertiary industry, has developed rapidly. The commercial sector has become an important driving force to promote the Gross Domestic Product (GDP) and electricity consumption [7]. Economic contribution and electricity consumption of the commercial sector in some developed areas have surpassed than that of the industrial sector [8]. Thus, it is crucial to encourage commercial enterprises to participate in DSM. Service activities, lighting, cooling, heating and office equipment related to different enterprises mainly contribute to the energy consumption [9].

DSM includes energy efficiency and demand response programs [10]. Efficiency improvement efforts at terminal power equipment are the most important in energy efficiency programs, including installing energy storage devices and applying energy-saving processes and equipment. Demand response refers to modification of electricity consumption patterns by end users in response to electricity price adjustments [4,11]. There are many techniques adopted in demand response programs, such as time-of-use price, critical-peak price, direct load control and interruptible load control [12]. It is essential to form a framework to evaluate DSM performances. Through an evaluation framework, authorities could measure the DSM implementation effects, control total energy consumption, promote optimal distribution of electric power resources and adjust differential electricity price policies.

Conventional sustainability contains three dimensions—economic development, social progress and environmental protection [13]. A framework for evaluating the DSM implementation effect will be established according to conventional concepts. For the economic dimension, benefits and costs of a DSM program including expenses occurred during project construction and operation, and the investment pay-back periods as well as electricity fee savings were considered. The impacts from the economic dimension reflected financial impacts from a DSM program at a micro level. For the social dimension, macro impacts on society development induced by some DSM programs such as contributions to the development of the energy industry, to power peak load shifting, to economic growth and avoidable electricity construction investment were included. For the environmental dimension, benefits from DSM such as greenhouse gas emission reduction, avoidable soil erosion and geological structure damage, and natural resource conservation were considered. Considering the importance and complexity of DSM techniques for program construction and operation, a technical dimension which reflects applications of the energy saving technology, was added to the evaluation framework [14,15]. For the technical dimension, factors including energy saving reconstruction technology for an energy system, distributed generation technology, technical staff training and DSM work processes construction were contained. The DSM performance evaluation are performed based on multiple criteria, thus can be considered as a multi-criteria decision making (MCDM) issue [16,17].

Various MCDM approaches have been proposed to evaluate DSM performance, including the scenario analysis method [18], the system dynamics model [19], the binary particle swarm optimization [20] and the simulation methods [21–23]. However, because these studies only contained a few evaluation indicators, these research results fail to reflect DSM performance comprehensively and miss subjective rating information for decision makings. To overcome the shortcomings, other techniques have been applied to evaluate overall DSM performance, including the analytic hierarchy process (AHP) [17,24], the entropy weight method [25] and the preference ranking organization methods for enrichment evaluations (PROMETHEE) [26].

AHP proposed by Saaty [27] is a suitable tool to clarify interdependent relationships among criteria using a hierarchical structure and boosts advantages in determining the weights of different criteria. The technique for order preference by similarity to an ideal solution (TOPSIS) has been employed to appraise DSM performance [28]. Because of the clear and logical operation processes of the TOPSIS, relative performances of each alternative can be obtained easily if criteria are complex and abundant. In view of the vagueness and intangibility resulting from poor information and human subjective judgments, fuzzy set theory should be employed to map linguistic ratings from decision makers to quantitative data [29,30]. Thus, we proposed a hybrid MCDM technique, namely the fuzzy AHP-TOPSIS approach, to evaluate DSM performance. The fuzzy AHP, proposed by Chang [31], was introduced to obtain criteria weights to measure the average importance of the information. In order to overcome the shortcomings of traditional TOPSIS in handling inherent ambiguity, Chen [32] combined traditional TOPSIS with a fuzzy set theory and developed a fuzzy TOPSIS to address the evaluation criteria with characteristics of the uncertainty from an MCDM. DSM performance can be finally ranked using the fuzzy TOPSIS.

The main contributions of this paper are:

(1) To the best of our knowledge, this is the first study on DSM performance in the commercial sector. We provided a detailed and complete evaluation list of economic, social, environmental and technical criteria to evaluate the DSM effects.
(2) The fuzzy AHP and the fuzzy TOPSIS methods have been employed in many research fields [28–32] and have good effects in decision-making procedures of alternatives evaluation. As we know, this is a hybrid MCDM model based on combining the fuzzy AHP weight method with the fuzzy TOPSIS approach. We have introduced the model into DSM performance evaluation and extended the application fields of these methods.
(3) Since experts with diverse professional backgrounds may give different decisions, it is necessary to probe the influences of sub-criteria weights on final decision-making. We gave a novel sensitivity analysis to research the performance of economic, social, environmental and technological criteria for DSM performance evaluation by modifying the sub-criteria weights.

2. Methods

2.1. Fuzzy Set Theory and Fuzzy Numbers

Fuzzy set theory, introduced by Zadeh [33], can be employed to deal with the imprecision and vagueness under an uncertain environment [34]. A fuzzy set, as a class of objects, is characterized by a membership function with a continuum of grades. Each object is assigned a grade of membership among (0, 1). If the membership value is one, the object belongs to the set completely. If the value is zero, the object does not belong to the set. If the value is between zero and one, the object belongs partially to the set. Fuzzy set theory can be employed to map qualitative information from human decisions to quantitative data. Linguistic ratings such as “poor”, “fair” and “good” are represented as numerical intervals.

Fuzzy numbers can be used to transform the qualitative judgments into quantitative data. Some mathematical operators and measurement methods are introduced in a vague decision domain. A triangular fuzzy number (TFN) is the most common type in applications due to their operational simplicity. A TFN is designated as a triplet $\widetilde{a} = (a^L, a^M, a^R)$, where a^L, a^M and a^R represent the smallest value, the middle value and the largest value for the evaluation objects [35]. These values are all real numbers. A TFN is shown in Figure 1. Let x represent the value in real number field, the membership function $\mu(x)$ can be:

$$\mu(x) = \begin{cases} (x - a^L)/(a^M - a^L) & a^L \leq x < a^M \\ (a^R - x)/(a^R - a^M) & a^M \leq x \leq a^R \\ 0 & x < a^L \text{ or } x > a^R \end{cases} \quad (1)$$

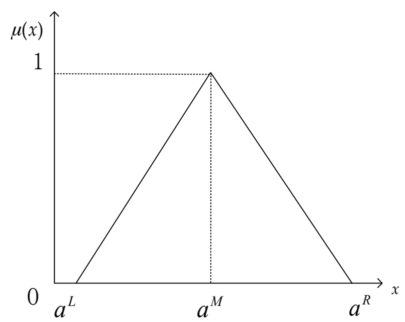

Figure 1. A triangular fuzzy number.

In order to obtain clear information, some defuzzification methods should be applied to transfer fuzzy numbers to crisp values with element characteristics in fuzzy sets. The graded mean integration representation (GMIR) method is employed to transfer TFNs into crisp numbers in order to avoid vagueness [36,37]. The graded mean integration representation value $T(\widetilde{a})$ of $\widetilde{a}$ is:

$$T(\widetilde{a}) = \frac{a^L + 4a^M + a^R}{6} \tag{2}$$

2.2. Fuzzy AHP Weighting Method

Due to fuzzy pairwise comparisons of criteria from decision makers, fuzzy AHP was applied to obtain the weights suitably [38]. Procedures of the criteria weights determination using the fuzzy AHP method are:

Step 1: Establish a hierarchy structure model. Due to complex determination of an evaluation index system resulting from various criteria, mass data and decision-making information, a hierarchy structure of the evaluation criteria should be formed according to characteristics of a MCDM issue [39]. The hierarchy structure consists of a goal layer, the main criteria layer and the sub-criteria layer, as shown in Figure 2.

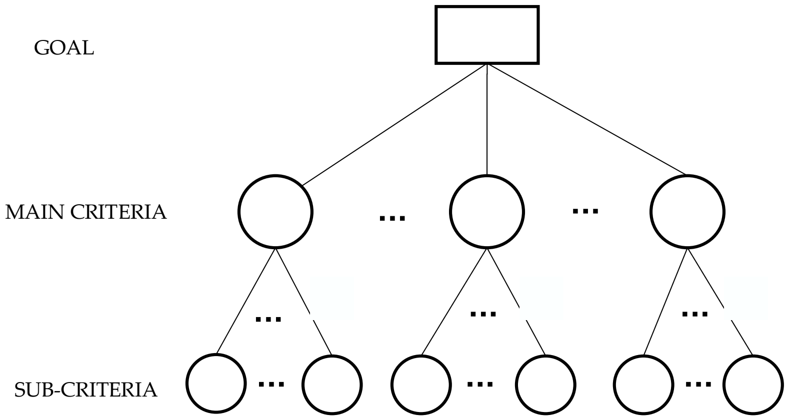

Figure 2. The hierarchical structure of AHP for determining the criteria weights.

Step 2: Obtain pairwise comparisons from expert groups and assemble individual fuzzy comparison matrices for the main criteria layer and the sub-criteria layer, respectively. We can clear the relative importance of the criteria according to these matrices. First, a questionnaire should be designed and distributed to all of the expert groups for obtaining the pairwise comparative judgments of each layer. These judgments are expressed as linguistic variables with TFNs used by Chang [31], as shown in Table 1 and Figure 3. Rankings for the criteria importance given by the expert groups are depicted in Figure 3. Second, these individual fuzzy comparison matrices are formed at all levels. Let $\widetilde{a}_{ij}^k$ represent the TFN corresponding to the pairwise comparative judgments of criterion i to j $(i, j = 1, \cdots, n)$ from expert group k. In order to assemble individual fuzzy comparison matrices, some rules should be listed: If $i > j$, $\widetilde{a}_{ij}^k$ corresponds to the TFNs in Table 1. If $i < j$, $\widetilde{a}_{ij}^k$ is the reciprocal TFNs due to the symmetry on the individual fuzzy comparison matrix. If $i = j$, $\widetilde{a}_{ij}^k$ is $(1, 1, 1)$. The individual fuzzy comparison matrix W^k of expert group k is:

$$W^k = \begin{vmatrix} \widetilde{a}_{11}^k & \widetilde{a}_{12}^k & \cdots & \widetilde{a}_{1n}^k \\ \widetilde{a}_{21}^k & \widetilde{a}_{22}^k & \cdots & \widetilde{a}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{a}_{n1}^k & \widetilde{a}_{n2}^k & \cdots & \widetilde{a}_{nn}^k \end{vmatrix}_{n \times n} \tag{3}$$

Table 1. Linguistic variables for evaluating the weights of the criteria.

Linguistic Terms	TFNs	Reciprocal TFNs	Meaning
Equally important (EI)	(1/2,1,3/2)	(2/3,1,2)	Criterion *i* is as important as criterion *j*
Moderately more important (MI)	(1,3/2,2)	(1/2,2/3,1)	Criterion *i* is moderately more important than criterion *j*
Strongly more important (SI)	(3/2,2,5/2)	(2/5,1/2,2/3)	Criterion *i* is strongly more important than criterion *j*
Very strongly more important (VI)	(2,5/2,3)	(1/3,2/5,1/2)	Criterion *i* is very strongly more important than criterion *j*
Absolutely important (AI)	(5/2,3,7/2)	(2/7,1/3,2/5)	Criterion *i* is absolutely more important than criterion *j*

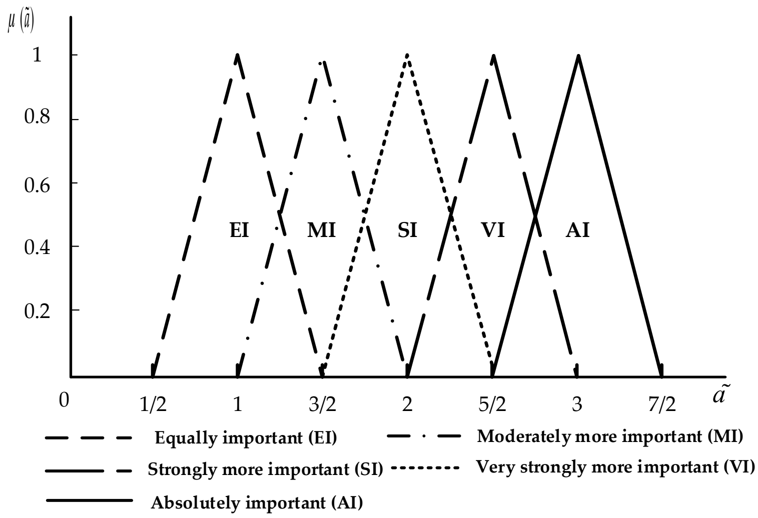

Figure 3. Linguistic variables for the importance rankings of criteria weights.

It is important to test the consistency of the fuzzy comparison matrices. The TFNs in these matrices should be transformed into $T(\tilde{a})$ using Equation (2) at first. If the largest eigenvalue $\lambda_{\max}$ of each matrix is the criteria number n, it is consistent according to Saaty [40]. Consistency index (CI) can be used to measure the deviation of the individual fuzzy comparison matrix away from the consistency and is:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \quad (4)$$

The accuracy of the CI will be reduced if the criteria number increases. For overcoming the shortcoming, random index (RI) and consistency ratio (CR) ware introduced to directly verify the consistency of the fuzzy comparison matrices [41]. The RI values are only related with the order of fuzzy comparison matrix and can be obtained applying the software of MATLAB: first, 1000 n-order reciprocal matrices were formed randomly using 2/7, 1/3, 2/5, 1/2, 2/3, 1, 3/2, 2, 5/2, 3, and 7/2; then, average k of their eigenvalues was calculated and the RI value for n-order reciprocal matrices is:

$$\mathrm{RI} = \frac{k - n}{n - 1} \quad (5)$$

The RI values for different orders can be computed through repeating the above processes and are listed in Table 2. The CR is:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \quad (6)$$

Experiential threshold 0.2 is commonly regarded as the upper limit for CR of a fuzzy comparison matric [41]. If the CR value is less than 0.2, this matric is consistent approximately.

Table 2. The values of RI.

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.45	1.49	1.52	1.54	1.56	1.57	1.58

Step 3: Form the aggregated fuzzy comparison matrices by the geometric mean method in order to obtain comprehensive importance for the criteria. Let $\widetilde{a}_{IJk} = (a^L_{IJk}, a^M_{IJk}, a^R_{IJk})$ be criterion I over J given by expert decision group k in the main criteria layer, $\widetilde{a}_{ijk} = (a^L_{ijk}, a^M_{ijk}, a^R_{ijk})$ be criterion i over j given by expert decision group k in the sub-criteria layer $k = 1, \cdots, V$, $I, J = 1, \cdots, m$ and $i, j = 1, \cdots, n$. The aggregated TFN $\widetilde{a}_{IJ} = (a^L_{IJ}, a^M_{IJ}, a^R_{IJ})$ of I over J in the main criteria layer is:

$$\widetilde{a}_{IJ} = (a^L_{IJ}, a^M_{IJ}, a^R_{IJ}) = (\sum_{k=1}^{V} \frac{a^L_{IJk}}{V}, \sum_{k=1}^{V} \frac{a^M_{IJk}}{V}, \sum_{k=1}^{V} \frac{a^R_{IJk}}{V}) \tag{7}$$

and the aggregated TFN $\widetilde{a}_{ij} = (a^L_{ij}, a^M_{ij}, a^R_{ij})$ of i over j in the sub-criteria layer is:

$$\widetilde{a}_{ij} = (a^L_{ij}, a^M_{ij}, a^R_{ij}) = (\sum_{k=1}^{V} \frac{a^L_{ijk}}{V}, \sum_{k=1}^{V} \frac{a^M_{ijk}}{V}, \sum_{k=1}^{V} \frac{a^R_{ijk}}{V}). \tag{8}$$

The aggregated fuzzy comparison matrices of the main criteria layer ($\overline{W}^{main}$) and the sub-criteria layer ($\overline{W}^{sub}$) are:

$$\overline{W}^{main} = (\widetilde{a}_{IJ})_{m\times m} \tag{9}$$

$$\overline{W}^{sub} = (\widetilde{a}_{ij})_{n\times n} \tag{10}$$

Step 4: Calculate values of fuzzy synthetic extent by summing the row vectors of the aggregated fuzzy comparison matrices. Let the fuzzy synthetic extent of criterion I for the main criteria layer H^{main}_I be represented as $(h^{mL}_I, h^{mM}_I, h^{mR}_I)$ and the fuzzy synthetic extent of criterion I for the sub-criteria layer H^{sub}_i be represented as $(h^{sL}_i, h^{sM}_i, h^{sR}_i)$. H^{main}_I and H^{sub}_i are:

$$H^{main}_I = \sqrt[m]{\prod_{J}^{m} \widetilde{a}_{IJ}} \tag{11}$$

$$H^{sub}_i = \sqrt[n]{\prod_{j}^{n} \widetilde{a}_{ij}} \tag{12}$$

where $h^{mL}_I = \sqrt[m]{\prod_{J=1}^{m} a^L_{IJ}}$, $h^{mM}_I = \sqrt[m]{\prod_{J=1}^{m} a^M_{IJ}}$, $h^{mL}_I = \sqrt[m]{\prod_{J=1}^{m} a^R_{IJ}}$; and $h^{sL}_i = \sqrt[n]{\prod_{j=1}^{n} a^L_{ij}}$, $h^{sM}_i = \sqrt[n]{\prod_{j=1}^{n} a^M_{ij}}$, $h^{sL}_i = \sqrt[n]{\prod_{j=1}^{n} a^R_{ij}}$.

Step 5: Transform the fuzzy synthetic extent values of the criteria to graded mean integration representation values by using Equation (2) in order to avoid the synthetic extent fuzziness. For main criterion I, the synthetic extent T^{main}_I is:

$$T^{main}_I = (h^{mL}_I + 4h^{mM}_I + h^{mR}_I)/6 \tag{13}$$

For sub-criterion i, the synthetic extent T_i^{sub} is:

$$T_i^{sub} = (h_i^{sL} + 4h_i^{sM} + h_i^{sR})/6 \tag{14}$$

Step 6: Calculate the main criterion weight w_I^{main} and the sub-criterion local weight w_i^{sub} according to the hierarchy structure:

$$w_I^{main} = T_I^{main} \times \left(\sum T_I^{main}\right)^{-1} \tag{15}$$

$$w_i^{sub} = T_i^{sub} \times \left(\sum T_i^{sub}\right)^{-1} \tag{16}$$

Step 7: Calculate the global weights of sub-criteria. Let w_i^{SG} be the global weight of sub-criterion i, and w_i^{sub} be the main criterion weight located in the parent node of the main criteria layer. The global weight w_i^{SG} of sub-criterion i is:

$$w_i^{SG} = w_I^{main} \times w_i^{sub} \tag{17}$$

2.3. Fuzzy TOPSIS Method

For uncertainty and imprecision of subjective judgments, the preference of alternatives were rated using linguistic ratings with respect to subjective criteria. Linguistic variables developed by Chen [33] were used to rate the subjective criteria performance, as listed in Table 3 and depicted in Figure 4. For objective criteria, the values of alternatives are expressed in TFNs.

Table 3. Linguistic variables for evaluating the ratings of subjective criteria.

Linguistic Terms	FTNs
Very Poor (VP)	(0,0,0.2)
Poor (P)	(0,0.2,0.4)
Good (G)	(0.3,0.5,0.7)
Very Good (VG)	(0.6,0.8,1)
Excellent (E)	(0.8,1,1)

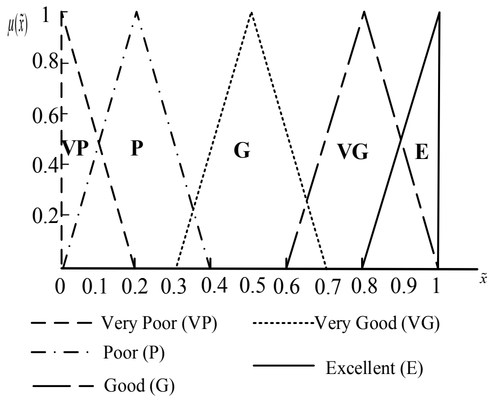

Figure 4. Linguistic variables for the ratings of subjective criteria.

The fuzzy TOPSIS approach comprises:

Step 1: Aggregate the linguistic ratings of alternatives given by V expert groups to obtain comprehensive fuzzy ratings. Suppose that there are n alternatives $O = \{O_1, O_2, \cdots, O_n\}$ to be prioritized, m criteria performance are determined by linguistic variables. Let $\tilde{x}_{ir}^k = (x_{ir}^{kL}, x_{ir}^{kM}, x_{ir}^{kR})$ be the fuzzy rating for criterion i of alternative r given by expert group k according to Table 3, $x_{ir}^{kL}, x_{ir}^{kM}, x_{ir}^{kR}$

represent the smallest value, the middle value and the largest value, $i = 1, \cdots, m$, $r = 1, \cdots, n$ and $k = 1, \cdots, V$. The aggregate fuzzy rating $\widetilde{x}_{ir} = (x_{ir}^L, x_{ir}^M, x_{ir}^R)$ for criterion i of alternative r is:

$$\widetilde{x}_{ir} = \frac{1}{V}\sum_{k=1}^{V}\widetilde{x}_{ir}^{k} = (\frac{1}{V}\sum_{k=1}^{V}x_{ir}^{kL}, \frac{1}{V}\sum_{k=1}^{V}x_{ir}^{kM}, \frac{1}{V}\sum_{k=1}^{V}x_{ir}^{kR}) \tag{18}$$

Step 2: Establish the initial fuzzy decision matrix $\boldsymbol{D}$ for alternatives according to actual objective data and fuzzy subjective ratings, as expressed in:

$$\boldsymbol{D} = \begin{bmatrix} \widetilde{x}_{11} & \widetilde{x}_{12} & \cdots & \widetilde{x}_{1n} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & \cdots & \widetilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \widetilde{x}_{m1} & \widetilde{x}_{m2} & \cdots & \widetilde{x}_{mn} \end{bmatrix} = \begin{bmatrix} (x_{11}^L, x_{11}^M, x_{11}^R) & (x_{12}^L, x_{12}^M, x_{12}^R) & \cdots & (x_{1n}^L, x_{1n}^M, x_{1n}^R) \\ (x_{21}^L, x_{21}^M, x_{21}^R) & (x_{22}^L, x_{22}^M, x_{22}^R) & \cdots & (x_{2n}^L, x_{2n}^M, x_{2n}^R) \\ \vdots & \vdots & \vdots & \vdots \\ (x_{m1}^L, x_{m1}^M, x_{m1}^R) & (x_{m2}^L, x_{m2}^M, x_{m2}^R) & \cdots & (x_{mn}^L, x_{mn}^M, x_{mn}^R) \end{bmatrix} \tag{19}$$

Step 3: Normalize an initial fuzzy decision matrix using the linear scaling transformation. Different indicators may hold different features generally. Some indicators hold the benefit-type feature, namely the higher the better. While others hold the cost-type feature, namely the lower the better. The normalization processes for all indicators are needed to avoid dimensional differences and ensure mathematical compatibility. Let $\widetilde{y}_{ir}$ be the normalized TFN of criterion i for alternative r, donated by $(y_{ir}^L, y_{ir}^M, y_{ir}^R)$. For a benefit-type indicator, the normalization processing is:

$$\widetilde{y}_{ir} = (\frac{x_{ir}^L}{u_i^+}, \frac{x_{ir}^M}{u_i^+}, \frac{x_{ir}^R}{u_i^+}) \text{ and } u_i^+ = \max_r\{x_{ir}^R\} \tag{20}$$

For a cost-type indicator, the normalization processing is:

$$\widetilde{y}_{ir} = (\frac{u_i^-}{x_{ir}^R}, \frac{u_i^-}{x_{ir}^M}, \frac{u_i^-}{x_{ir}^L}) \text{ and } u_i^- = \min_r\{x_{ir}^L\} \tag{21}$$

And the normalized fuzzy decision matrix $\overline{\boldsymbol{D}}$ can be:

$$\overline{\boldsymbol{D}} = \begin{bmatrix} \widetilde{y}_{11} & \widetilde{y}_{12} & \cdots & \widetilde{y}_{1n} \\ \widetilde{y}_{21} & \widetilde{y}_{22} & \cdots & \widetilde{y}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \widetilde{y}_{m1} & \widetilde{y}_{m2} & \cdots & \widetilde{y}_{mn} \end{bmatrix} = \begin{bmatrix} (y_{11}^L, y_{11}^M, y_{11}^R) & (y_{12}^L, y_{12}^M, y_{12}^R) & \cdots & (y_{1n}^L, y_{1n}^M, y_{1n}^R) \\ (y_{21}^L, y_{21}^M, y_{21}^R) & (y_{22}^L, y_{22}^M, y_{22}^R) & \cdots & (y_{2n}^L, y_{2n}^M, y_{2n}^R) \\ \vdots & \vdots & \vdots & \vdots \\ (y_{m1}^L, y_{m1}^M, y_{m1}^R) & (y_{m2}^L, y_{m2}^M, y_{m2}^R) & \cdots & (y_{mn}^L, y_{mn}^M, y_{mn}^R) \end{bmatrix} \tag{22}$$

Step 4: Build a weighted normalized fuzzy decision matrix $\mathbf{Z}$ to contain the importance of the criteria. It can be obtained by multiplying the global sub-criterion weight w_i^{SG} by $\widetilde{y}_{ir}$ of the normalized fuzzy decision matrix $\overline{\boldsymbol{D}}$,

$$\begin{aligned} \mathbf{Z} &= \begin{bmatrix} w_1^{SG} \otimes \widetilde{y}_{11} & w_2^{SG} \otimes \widetilde{y}_{12} & \cdots & w_n^{SG} \otimes \widetilde{y}_{1n} \\ w_1^{SG} \otimes \widetilde{y}_{21} & w_2^{SG} \otimes \widetilde{y}_{22} & \cdots & w_n^{SG} \otimes \widetilde{y}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1^{SG} \otimes \widetilde{y}_{m1} & w_2^{SG} \otimes \widetilde{y}_{m2} & \cdots & w_n^{SG} \otimes \widetilde{y}_{mn} \end{bmatrix} \\ &= \begin{bmatrix} (w_1^{SG}y_{11}^L, w_1^{SG}y_{11}^M, w_1^{SG}y_{11}^R) & (w_2^{SG}y_{12}^L, w_2^{SG}y_{12}^M, w_2^{SG}y_{12}^R) & \cdots & (w_n^{SG}y_{1n}^L, w_n^{SG}y_{1n}^M, w_n^{SG}y_{1n}^R) \\ (w_1^{SG}y_{21}^L, w_1^{SG}y_{21}^M, w_1^{SG}y_{21}^R) & (w_2^{SG}y_{22}^L, w_2^{SG}y_{22}^M, w_2^{SG}y_{22}^R) & \cdots & (w_n^{SG}y_{2n}^L, w_n^{SG}y_{2n}^M, w_n^{SG}y_{2n}^R) \\ \vdots & \vdots & \vdots & \vdots \\ (w_1^{SG}y_{m1}^L, w_1^{SG}y_{m1}^M, w_1^{SG}y_{m1}^R) & (w_2^{SG}y_{m2}^L, w_2^{SG}y_{m2}^M, w_2^{SG}y_{m2}^R) & \cdots & (w_n^{SG}y_{mn}^L, w_n^{SG}y_{mn}^M, w_n^{SG}y_{mn}^R) \end{bmatrix} \end{aligned} . \tag{23}$$

The global weights for all sub-criteria can be obtained using the fuzzy AHP method.

Step 5: Define the fuzzy positive ideal solution $\mathbf{Z}^+$ and the fuzzy negative ideal solution $\mathbf{Z}^-$. Let T_1 represent the benefit-type indicator set, T_2 represent the cost-type indicator set, $\widetilde{z}_i^+ = (z_i^{+L}, z_i^{+M}, z_i^{+R})$ and $\widetilde{z}_i^- = (z_i^{-L}, z_i^{-M}, z_i^{-R})$ represent the fuzzy positive ideal solution and the fuzzy negative ideal solution for criterion i. $\mathbf{Z}^+$ and $\mathbf{Z}^-$ are:

$$\mathbf{Z}^+ = (\widetilde{z}_i^+) = \left\{ \left(\max_r \widetilde{z}_{ir} \middle| i \in T_1 \right), \left(\min_r \widetilde{z}_{ir} \middle| i \in T_2 \right) \right\} \tag{24}$$

$$\mathbf{Z}^- = (\widetilde{z}_i^-) = \left\{ \left(\min_r \widetilde{z}_{ir} \middle| i \in T_1 \right), \left(\max_r \widetilde{z}_{ir} \middle| i \in T_2 \right) \right\} \tag{25}$$

where $\max_r \widetilde{z}_{ir} = (\max_r w_i^{Sub(global)} y_{ir}^L, \max_r w_i^{Sub(global)} y_{ir}^M, \max_r w_i^{Sub(global)} y_{ir}^R)$,
and $\min_r z_{ir} = (\min_r w_i^{Sub(global)} y_{ir}^L, \min_r w_i^{Sub(global)} y_{ir}^M, \min_r w_i^{Sub(global)} y_{ir}^R)$.

Step 6: Compute the distances d_r^+ and d_r^- of each alternative from $\mathbf{Z}^+$ and $\mathbf{Z}^-$ respectively. Let $d_z(\cdot,\cdot)$ represent the distance between two FTNs, d_r^+ and d_r^- are:

$$d_r^+ = \sum_{i=1}^{m} d_z(\widetilde{z}_{ir}, \widetilde{z}_i^+);\ d_r^- = \sum_{i=1}^{m} d_z(\widetilde{z}_{ir}, \widetilde{z}_i^-) \tag{26}$$

According to Chen [32], the performance of the best alternative r is father from $\mathbf{Z}^-$ and closer to $\mathbf{Z}^+$ than others. Some approaches have been used to compute the distance between two TFNs. The *L2*-metric distance approach is employed for easy implementation [42]. The distance $d\left(\widetilde{z}_i, \widetilde{z}_j\right)$ between $\widetilde{z}_i$ and $\widetilde{z}_j$ is:

$$d\left(\widetilde{z}_i, \widetilde{z}_j\right) = \left\{ \left[\left(z_i^L - z_j^L\right)^2 + 4 \times \left(z_i^M - z_j^M\right)^2 + \left(z_i^R - z_j^R\right)^2 \right] / 6 \right\}^{1/2} \tag{27}$$

Thus, the distances d_r^+ and d_r^- of each alternative from $\widetilde{z}_i^+$ and $\widetilde{z}_i^-$ are:

$$d_r^+ = \sum_{j=1}^{m} \left\{ \left[\left(z_{ir}^L - z_i^{+L}\right)^2 + 4 \times \left(z_{ir}^M - z_i^{+M}\right)^2 + \left(z_{ir}^R - z_i^{+R}\right)^2 \right] / 6 \right\}^{1/2} \tag{28}$$

$$d_r^- = \sum_{i=1}^{m} \left\{ \left[\left(z_{ir}^L - z_i^{-L}\right)^2 + 4 \times \left(z_{ir}^M - z_i^{-M}\right)^2 + \left(z_{ir}^R - z_i^{-R}\right)^2 \right] / 6 \right\}^{1/2} \tag{29}$$

Step 7: Compute the closeness coefficient value (CC_r) of each alternative:

$$CC_r = \frac{d_r^-}{d_r^+ + d_r^-} \tag{30}$$

The closeness coefficient emphasizes the distances close to the fuzzy positive solution $\mathbf{Z}^+$ and away from the fuzzy negative ideal solution $\mathbf{Z}^-$, which is denoted by the scope of (0, 1). Alternatives can be ranked according to the closeness coefficient values. The alternative with closest to $\mathbf{Z}^+$ and farthest to $\mathbf{Z}^-$ should be selected as the best one.

2.4. The Framework of Proposed Hybrid Fuzzy AHP-TOPSIS Model

The proposed fuzzy AHP-TOPSIS model to evaluate the DSM performance involves the following three phases, as shown in Figure 5.

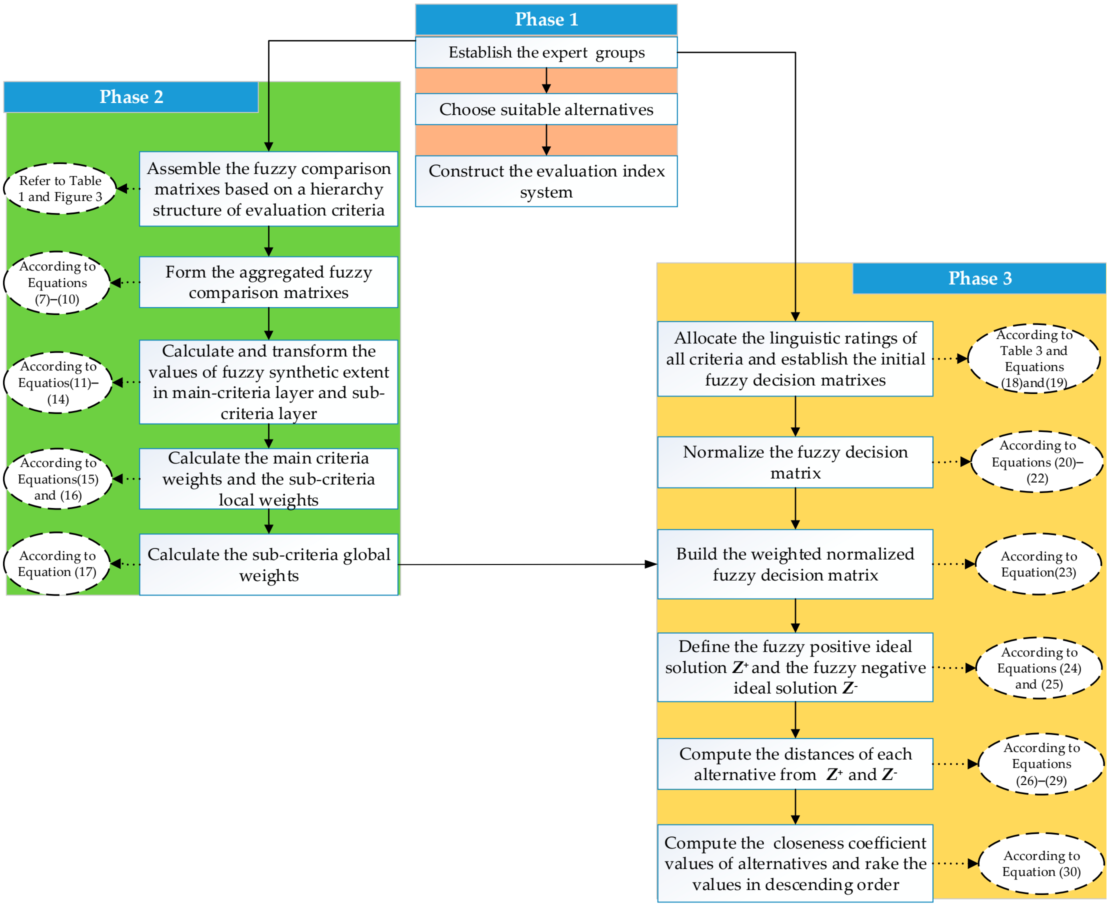

Figure 5. Fuzzy-AHP-TOPSIS based MCDM framework for DSM performance evaluation.

Phase 1: Identify evaluation criteria and construct an index system. An appropriate expert decision group was established to evaluate the criteria performance. According to experts' recommendations and enterprises characteristics, an appropriate evaluation index system was constructed from a sustainability perspective.

Phase 2: Determine the weights of the evaluation criteria based on the fuzzy AHP approach. A hierarchy structure for the evaluation index system was conducted and the fuzzy AHP method was employed to determine the sub-criteria weights. First, executives, managers and experts affiliated to the expert groups estimated the relative pairwise comparisons by using linguistic ratings with the TFNs (as listed in Table 1) and a fuzzy pairwise comparison matrix of each expert was formed. The consistency of the matrix was checked to ensure the reliability of the criteria weights. Second, a fuzzy comparison matrix was aggregated according to Equations (6)–(9). Then, fuzzy synthetic extent of each criterion was integrated by using Equations (10)–(13). Final, the main criteria weights and the sub-criteria global weights were calculated according to Equations (14)–(16).

Phase 3: Evaluate the DSM performance by using the fuzzy TOPSIS method. First, the fuzzy linguistic ratings were allocated to all potential alternatives with respect to the subjective criteria given by expert groups according to Table 3. Second, the fuzzy ratings of all alternatives with respect to the objective criteria were transferred into TFNs based on actual situation. Then, an initial fuzzy decision matrix was established. At last, the fuzzy TOPSIS approach was employed to assemble the fuzzy ratings of the criteria for all alternatives in order to calculate rating result of each potential alternative (namely commercial enterprise). Closeness coefficient values of all potential alternatives were ranked in a descending order. The higher the closeness coefficient value was, the better the DSM performance of potential commercial enterprise was.

The proposed hybrid MCDM approach based on the fuzzy AHP and the fuzzy TOPSIS approaches have the following advantages. First, the applications of FTNs and linguistic ratings were used to overcome partial or lacking quantitative data and transfer qualitative judgments into computable data. Then, the fuzzy AHP weighting approach could reflect experts' recommendations by the linguistic ratings and represent the average importance of the evaluation criteria by the hierarchy structure. At last, the fuzzy TOPSIS approach was applied to deal with insufficient quantitative data by using the linguistic ratings. The proposed hybrid MCDM approach is much more suitable to handle practical decision-making issues.

3. Evaluation Index System for the DSM Performance of Commercial Enterprises

An evaluation index system is particularly important to evaluate the DSM effect. It is vital to adopt a series of criteria into the evaluation index system to reflect the inherent characteristics of DSM. However, as the program implementations by these enterprises are in primary stages in China, there are no consistent criteria to measure the performance. We try to establish the evaluation index system to achieve sustainable development.

According to the conventional sustainability theory, sustainable development should be measured through economic, social and environmental dimensions. Moreover, since the DSM implementation involves complex technical conditions, a technical dimension was included to develop the original theory. Therefore, the evaluation index system included economy, society, environment and technology criteria, which were the main criteria based on Figure 2. Further, sub-criteria affiliated with the above four main criteria were determined by the follows: first, initial evaluation sub-criteria were built by referring to the Sustainability Reporting Guidelines of Global Reporting Initiative and Chinese Corporate Social Responsibility Reporting Guidelines; second, some experts from the fields of economy, society, environment and technology reviewed the initial evaluation sub-criteria and selected vital ones according to their experiences and expertise; at last, less important sub-criteria were removed and the final sub-criteria were built. The final evaluation index system is shown in Figure 6, including 15 sub-criteria. Detailed explanations of the sub-criteria are as below.

3.1. Economic Criteria (A1)

For the economic criteria, project investment and related cost should be considered. Alternatively, DSM effects in energy conservation and enterprise service quality need to be taken into consideration. Five sub-criteria affiliated with the economic criteria were selected to assess the DSM performance.

(1) Electricity savings (C1): Measure the reduction of the electricity consumption per unit area by implementing DSM. Appropriate energy efficient programs can help the enterprises achieve their goals to save energy.
(2) A DSM investment pay-back period (C2): Refers to total investment cost of DSM divided by monthly returns. This sub-criterion measures the economic benefit for enterprises.
(3) Loss aversion related to forced outage (C3): Refers to losses from service interruptions caused by forced outage. The forced outage probability can be reduced if an enterprise participates in DSM.
(4) Customer satisfaction with enterprise services (C4): Measures the impacts on customers' subjective enjoyment for the services provided under DSM implementation. For the commercial sector, higher customer satisfaction brings more business profits.
(5) Enterprise financing ability (C5): Refers to financing channels and fundraising scales faced by these enterprises. A lot of capital investment is required for DSM implementation.

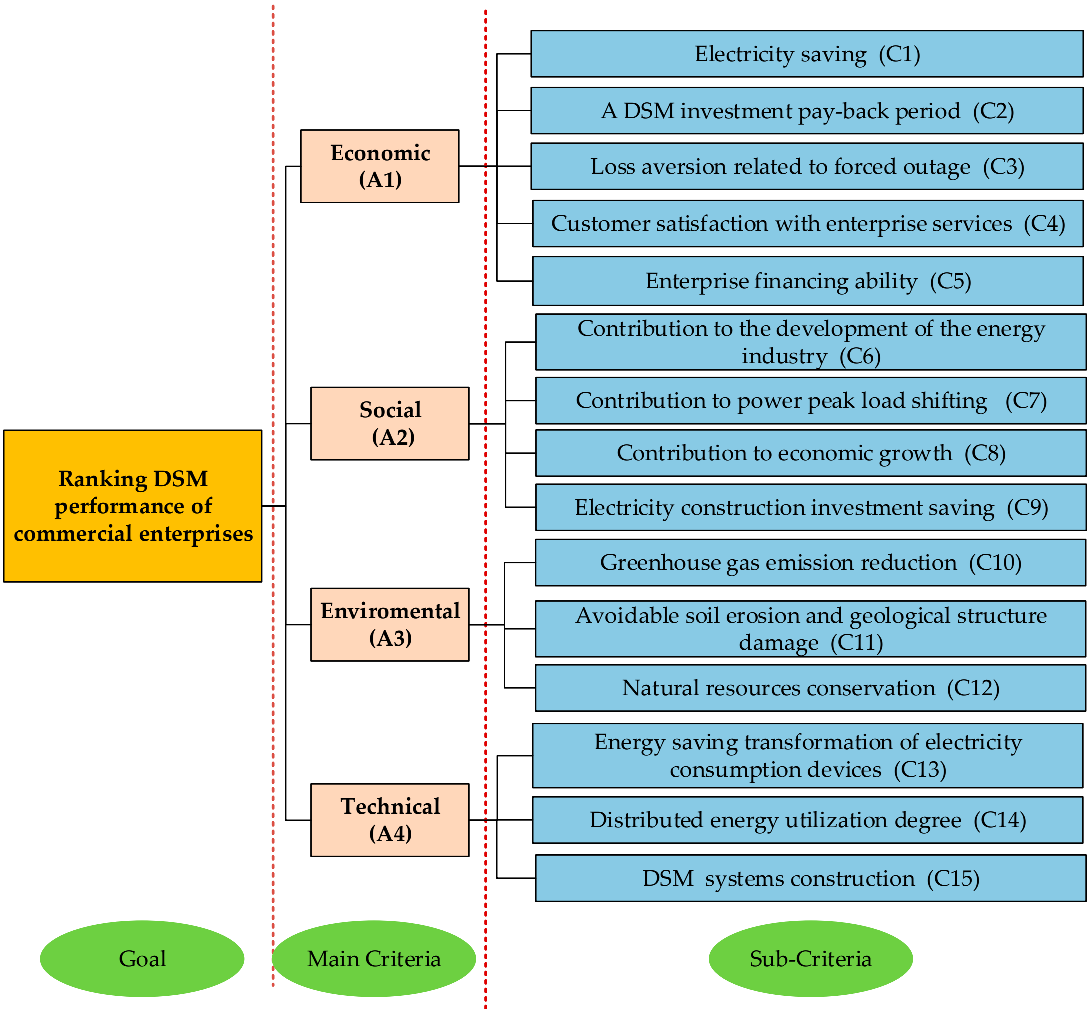

Figure 6. Evaluation index system for DSM performance.

3.2. Social Criteria (A2)

Four sub-criteria affiliated with the society criteria were finally chosen, which reflect the impacts on the commercial sector under the DSM implementation at macro levels of the whole society.

(1) Contribution to the development of the energy industry (C6): includes the energy saving service corporations, the distributed micro-grid systems etc.
(2) Contribution to power peak load shifting (C7): helps increase penetration of the renewable energy sources and improve operation reliability of the power grid.
(3) Contribution to economic growth (C8): Refers to the contribution degree of the DSM implementations to ensure energy supply security and maintain sustainable economic development.
(4) Electricity construction investment saving (C9): Measures avoidable power generation equipment investment due to the electricity consumption reduction and avoidable power grid investment due to the load transfer.

3.3. Environmental Criteria (A3)

Three sub-criteria affiliated with the environmental criteria were finally chosen into the index system.

(1) Greenhouse gas emission reduction (C10): Measures the reduction of the environmental pollutant (such as CO_2 and NO_2) emissions from the power generation sector due to DSM.

(2) Avoidable soil erosion and geological structure damage (C11): Measures the reduction of occurrence probability for soil erosion and geological structure damage benefiting from DSM.
(3) Natural resources conservation (C12): DSM is conducive to cutting the energy demand, which is good to save limited natural resources, especially fossil fuel [3]. This sub-criterion measures the reduction of the natural resources consumption by cutting the energy demand because of DSM.

3.4. Technical Criteria (A4)

These enterprises need to carry out technological innovation to implement DSM. The sub-criteria affiliated with the technical criteria were summarized into:

(1) Energy saving transformation of electricity consumption devices (C13): Measures the applications of energy saving equipment and technologies in a power system, including lighting, air conditioning and heating. The sub-criterion reflects energy saving technological levels of enterprises.
(2) Distributed energy utilization degree (C14): Refers to the application of a distributed energy technology into a cooling-heating-power combined cycle, which helps to improve the energy resources comprehensive utilization efficiency of the energy resources and the continuity and reliability of energy supply. The distributed power generation technology, the smart micro grid technology and the distributed energy storage technology are basically adopted by entrepreneurs [43].
(3) DSM systems construction (C15): Includes appointing directors, hiring full-time management personnel and training technical staff, which are based on enterprise status in order to ensure the effectiveness and continuity of DSM implementation.

4. Empirical Analysis

The commercial sector in Beijing has exceeded the industrial sector in terms of GDP. The city was selected as a DSM pilot city by China's Ministry of Finance and National Development and Reform Commission (NDRC) [8]. Beijing financial street, the gathering place of Chinese financial institutions, was identified as the key area of DSM implementation according to governmental plans. Four large-scale financial enterprises in the financial street were chosen as the empirical analysis objects. These were similar in terms of business scale, office area and office equipment and complied with peak valley electricity price standard. Meanwhile, these enterprises have implemented a series of programs, including LED lamp reconstruction, chilled water storage system establishment, energy saving optimization of air conditioning systems and high efficiency motor replacement. Four expert groups ($k = 1,2, \ldots, 4$) from government departments, research institutions, electricity utilities and the commercial sector were formed to obtain the linguistic preference ratings of alternatives.

4.1. Determine the Weights of All the Criteria based on the Fuzzy AHP Technique

Considering the DSM implementation of the four large-scale financial enterprise alternatives, all of the expert groups gave the comparative judgments of the criteria weights in the form of linguistic ratings according to Table 1. Let DM1, DM2, DM3 and DM4 represent the expert groups from government departments, research institutions, electricity utilities and commercial enterprises. The CR values for comparative matrices were computed and listed in Table 4. All of the CR values are below 0.2, through which we confirmed the consistency of comparative judgments given by each expert group.

Table 4. CR values of comparative matrices for all the levels.

CR	Goal	A1	A2	A3	A4
DM1	0.025	0.041	0.119	0.04	0.029
DM2	0.036	0.022	0.019	0.04	0.037
DM3	0.063	0.044	0.081	0.026	0.096
DM4	0.089	0.05	0.041	0.016	0.064

The fuzzy comparison matrices of all layers were aggregated according to Equations (7)–(10). The aggregated results are listed in Tables 5–9. The values of fuzzy synthetic extent were calculated and transformed according to Equations (11)–(14). The global weights of the criteria were computed according to Equations (15)–(17), as listed in Table 10.

Table 5. The aggregated fuzzy numbers of main criteria weights.

	A1	A2	A3	A4
A1	(1.0,1.0,1.0)	(1.125,1.625,2.125)	(0.575,0.792,1.085)	(1.25,1.75,2.25)
A2	(0.493,0.667,1.085)	(1.0,1.0,1.0)	(0.425,0.542,0.753)	(1.375,1.875,2.375)
A3	(1.125,1.542,2)	(1.375,1.875,2.375)	(1.0,1.0,1.0)	(1.625,2.043,2.50)
A4	(0.45,0.583,0.835)	(0.425,0.543,0.753)	(0.505,0.683,0.893)	(1.0,1.0,1.0)

Table 6. The aggregated fuzzy numbers of the ratings related to main criterion A1.

	C1	C2	C3	C4	C5
C1	(1,1,1)	(1,1.5,2)	(0.433,0.56,0.793)	(1.082,1.475,1.875)	(1.625,2.125,2.625)
C2	(0.935,1.25,1.918)	(1,1,1)	(0.365,0.45,0.585)	(0.875,1.2925,1.75)	(0.625,1.125,1.625)
C3	(1.25,1.75,2.25)	(1.75,2.25,2.75)	(1,1,1)	(1.625,2.0425,2.5)	(2.125,2.625,3.125)
C4	(0.825,1.0425,1.335)	(0.625,0.893,1.375)	(0.505,0.683,0.893)	(1,1,1)	(0.675,0.875,1.128)
C5	(0.383,0.475,0.628)	(0.585,0.835,1.5)	(0.323,0.39,0.493)	(1.225,1.625,2.043)	(1,1,1)

Table 7. The aggregated fuzzy numbers of the ratings related to main criterion A2.

	C6	C7	C8	C9
C6	(1,1,1)	(0.725,1.043,1.418)	(0.5,0.835,1.25)	(0.625,0.96,1.375)
C7	(0.893,1.25,1.793)	(1,1,1)	(0.725,0.96,1.293)	(1.125,1.543,2)
C8	(0.835,1.25,2)	(0.975,1.375,1.793)	(1,1,1)	(1,1.5,2)
C9	(0.793,1.168,1.75)	(0.575,0.793,1.085)	(0.5,0.67,1)	(1,1,1)

Table 8. The aggregated fuzzy numbers of the ratings related to main criterion A3.

	C10	C11	C12
C10	(1,1,1)	(1.5,2,2.5)	(0.75,1.25,1.75)
C11	(0.408,0.518,0.71)	(1,1,1)	(0.45,0.585,0.835)
C12	(0.585,0.835,1.5)	(1.25,1.75,2.25)	(1,1,1)

Table 9. The aggregated fuzzy numbers of the ratings related to main criterion A4.

	C13	C14	C15
C13	(1,1,1)	(0.5,1,1.5)	(1.125,1.625,2.125)
C14	(0.67,1,2)	(1,1,1)	(1,1.5,2)
C15	(0.475,0.628,0.918)	(0.518,0.71,1.168)	(1,1,1)

Table 10. The fuzzy synthetic extent values and the weights of the evaluation criteria.

Main Criteria	Fuzzy Synthetic Extent	Local Weight	Sub-Criteria	Fuzzy Synthetic Extent	Local Weight	Global Weight
A1	(0.948,1.225,1.509)	0.279	C1	(0.947,1.214,1.508)	0.214	0.060
			C2	(0.715,0.960,1.261)	0.170	0.047
			C3	(1.498,1.840,2.172)	0.322	0.090
			C4	(0.706,0.889,1.131)	0.158	0.044
			C5	(0.617,0.759,0.989)	0.136	0.038
A2	(0.732,0.908,1.180)	0.210	C6	(0.690,0.956,1.245)	0.223	0.047
			C7	(0.927,1.166,1.467)	0.272	0.057
			C8	(0.950,1.267,1.636)	0.296	0.062
			C9	(0.690,0.887,1.174)	0.209	0.044
A3	(1.259,1.559,1.856)	0.354	C10	(1.040,1.357,1.636)	0.423	0.150
			C11	(0.568,0.671,0.840)	0.214	0.076
			C12	(0.900,1.135,1.500)	0.363	0.128
A4	(0.557,0.682,0.865)	0.157	C13	(0.825,1.176,1.472)	0.373	0.059
			C14	(0.875,1.145,1.587)	0.376	0.059
			C15	(0.626,0.764,1.023)	0.251	0.039

4.2. Assemble the Initial Fuzzy Decision Matrix

The initial fuzzy decision matrix was established to integrate the original ratings .The TFNs for the objective criteria and the subjective criteria were assembled by the arithmetic mean method. C1 and C2 are objective sub-criteria for each alternative. The TFNs of C1 and C2 were obtained by collecting the actual data. The four expert groups were asked to give linguistic preference ratings of four alternatives (represented by O1, O2, O3 and O4) with respect to the subjective criteria except C1 and C2. The aggregate fuzzy linguistic ratings for each alternative can be computed by Equations (18) and (19). The initial fuzzy decision matrix $\boldsymbol{D}$ is:

$$D = \begin{array}{c} \begin{array}{cccc} \text{O1} & \text{O2} & \text{O3} & \text{O4} \end{array} \\ \begin{bmatrix} (0.081, 0.089, 0.096) & (0.077, 0.084, 0.091) & (0.071, 0.076, 0.088) & (0.07, 0.081, 0.095) \\ (0.056, 0.070, 0.089) & (0.061, 0.083, 0.111) & (0.061, 0.078, 0.101) & (0.078, 0.095, 0.117) \\ (0.15, 0.35, 0.55) & (0.225, 0.425, 0.625) & (0.075, 0.175, 0.375) & (0.075, 0.125, 0.325) \\ (0.35, 0.55, 0.7) & (0.35, 0.50, 0.65) & (0.425, 0.625, 0.775) & (0.65, 0.85, 1) \\ (0.15, 0.3, 0.5) & (0.15, 0.35, 0.55) & (0.375, 0.575, 0.775) & (0.65, 0.85, 1) \\ (0.075, 0.275, 0.475) & (0, 0.2, 0.4) & (0.3, 0.5, 0.7) & (0.375, 0.575, 0.775) \\ (0.075, 0.275, 0.475) & (0.075, 0.275, 0.475) & (0.45, 0.65, 0.85) & (0.575, 0.775, 0.925) \\ (0.225, 0.425, 0.625) & (0.15, 0.35, 0.55) & (0.45, 0.65, 0.85) & (0.7, 0.9, 1) \\ (0.225, 0.425, 0.625) & (0.15, 0.35, 0.55) & (0.375, 0.575, 0.775) & (0.65, 0.85, 1) \\ (0.3, 0.5, 0.7) & (0.075, 0.275, 0.475) & (0.575, 0.775, 0.925) & (0.7, 0.9, 1) \\ (0.375, 0.575, 0.775) & (0.225, 0.375, 0.575) & (0.575, 0.775, 0.925) & (0.65, 0.85, 1) \\ (0.3, 0.5, 0.7) & (0, 0.2, 0.4) & (0.525, 0.725, 0.925) & (0.7, 0.9, 1) \\ (0.3, 0.5, 0.7) & (0, 0.05, 0.25) & (0.375, 0.575, 0.775) & (0.575, 0.775, 0.925) \\ (0.075, 0.225, 0.425) & (0.15, 0.25, 0.45) & (0.35, 0.55, 0.7) & (0.575, 0.775, 0.925) \\ (0.075, 0.225, 0.425) & (0.075, 0.275, 0.475) & (0.375, 0.575, 0.775) & (0.7, 0.9, 1) \end{bmatrix} \end{array},$$

In D, each column vector represents the aggregate ratings of all the criteria for each alternative.

4.3. Calculate the Fuzzy Positive Ideal Solution and the Fuzzy Negative Ideal Solution

The fuzzy positive ideal solution and the fuzzy negative ideal solution should be computed to obtain the ranking results. Among the fifteen sub-criteria, C2 and C3 were cost-type criteria, and the rest were of benefit-type. The initial fuzzy decision matrix was normalized according to Equations (20)–(22). The weighted normalized fuzzy decision matrix $\boldsymbol{D}$ was obtained according to Equation (23). The fuzzy positive ideal solution $\mathbf{Z}^{+}$ and fuzzy negative ideal solution $\mathbf{Z}^{-}$ were calculated according to Equations (24) and (25), and are listed in Table 11.

Table 11. The fuzzy positive ideal solution and fuzzy negative ideal solution.

j	**C1**	**C2**	**C3**	**C4**	**C5**
$\tilde{z}_j^{+}$	(0.050,0.055,0.06)	(0.023,0.028,0.034)	(0.011,0.016,0.03)	(0.029,0.037,0.044)	(0.025,0.032,0.038)
$\tilde{z}_j^{-}$	(0.043,0.047,0.055)	(0.027,0.034,0.044)	(0.21,0.054,0.09)	(0.015,0.022,0.029)	(0.006,0.013,0.021)
j	**C6**	**C7**	**C8**	**C9**	**C10**
$\tilde{z}_j^{+}$	(0.023,0.035,0.047)	(0.036,0.048,0.057)	(0.043,0.056,0.062)	(0.029,0.037,0.044)	(0.105,0.135,0.15)
$\tilde{z}_j^{-}$	(0,0.012,0.024)	(0.005,0.014,0.026)	(0.009,0.022,0.034)	(0.007,0.015,0.024)	(0.011,0.034,0.064)
j	**C11**	**C12**	**C13**	**C14**	**C15**
$\tilde{z}_j^{+}$	(0.049,0.064,0.076)	(0.09,0.116,0.128)	(0.037,0.049,0.059)	(0.037,0.049,0.059)	(0.028,0.036,0.04)
$\tilde{z}_j^{-}$	(0.017,0.028,0.044)	(0,0.026,0.051)	(0,0.003,0.016)	(0.01,0.016,0.029)	(0.003,0.011,0.019)

4.4. Determine the Preference Rakings of the Alternatives

The distances of each alternative from the fuzzy positive ideal solution and the fuzzy negative ideal solution were calculated according to Equations (26)–(29):

$$d_1^{+} = 0.3481,\ d_2^{+} = 0.4727,\ d_3^{+} = 0.1863,\ d_4^{+} = 0.0447$$

$$d_1^{-} = 0.2277,\ d_2^{-} = 0.1483,\ d_3^{-} = 0.3377,\ d_4^{-} = 0.4351$$

The closeness coefficient for each alternative was calculated by using Equation (30). The results are:

$$CC_1 = 0.3954,\ CC_2 = 0.2388,\ CC_3 = 0.6445,\ CC_4 = 0.9068$$

The closeness coefficient values were ranked in decreasing order

$$CC_4 \succ CC_3 \succ CC_1 \succ CC_2$$

It is shown that O4 is the best alternative, followed by O3, O1 and O2.

5. Discussion

Alternative O4 was the best according to the above results. To obtain better insight from the fuzzy AHP-TOPSIS application on DSM performance evaluation, we will explore the impacts of sub-criteria weights and performance.

According to the normalized fuzzy decision matrix $\overline{\boldsymbol{D}}$, the sub-criteria performance of four alternatives are shown in Figure 7, which reflects the important information effectively considering the criteria type. The larger the sub-criteria value is, the better the alternative performance will be. Global weights of all sub-criteria were drawn in Figure 8.

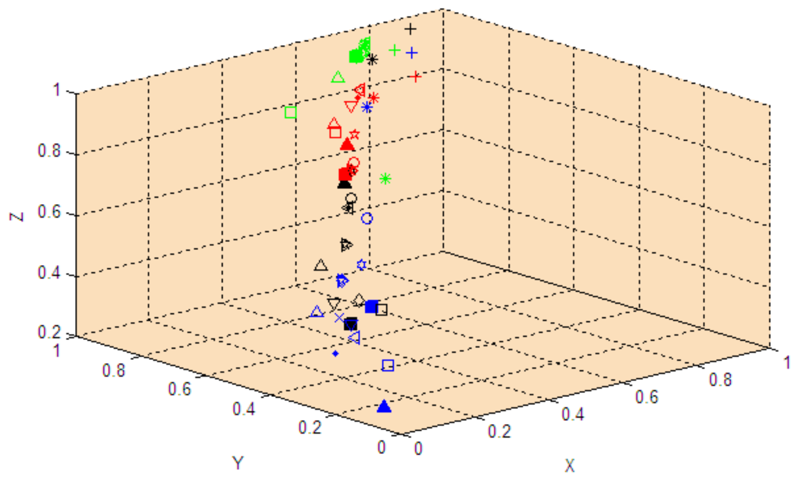

Figure 7. The sub-criteria performance of four alternatives. Note: (1) '+', '✱', '□', '○', '◇', '△', '▽', '☆', '▷', '◁', '✡', '•', '▲', '■', and '×' represent the performance of C1, C2, C3, C4, C5, C6, C7, C8, C9, C10, C11, C12, C13, C14 and C15, respectively; (2) **black**, **blue**, **red** and **green** represent alternatives O1, O2, O3 and O4, respectively; and (3) *X*-axis, *Y*-axis and *Z*-axis represent the smallest value, middle value and largest value of sub-criteria performance, respectively.

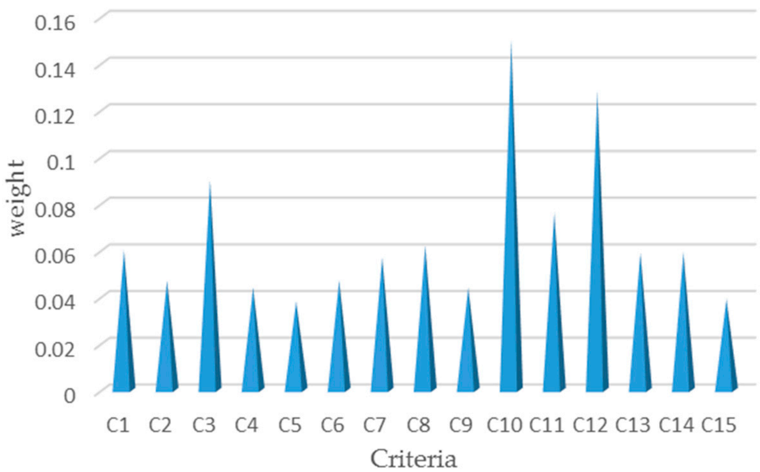

Figure 8. The global weights of the sub-criteria.

It is shown that for alternative O4 (marked in green in Figure 7), the sub-criteria except C1 and C2 have the best performance compared to that of other three alternatives. Meanwhile, the weight values of C1 and C2 are medium (rank No. 6 for C1 and No. 10 for C2 as shown in Figure 7). O4 is regarded as the best one among all alternatives according to the overall rankings. For alternative O3 (marked in red in Figure 7), majority sub-criteria except C1 have good performance. Considering the weights, O3 ranks the second among all the alternatives. For O2 (marked in blue in Figure 7), eleven sub-criteria present the poorest performance. Considering the weight values, O2 is the worst alternative among all alternatives. From Figure 8, it is shown that C10, C11, and C12 affiliated with the environmental criteria, C3 affiliated with the economic criteria and C8 affiliated with the social criteria attracted more attention from the expert groups. Conversely, C4 and C5 affiliated with the economic criteria, C9 affiliated with the social criteria and C15 affiliated with the technical criteria are relatively less important. This result reflects that the public has realized the importance of protecting the living environment. More and more serious environmental problems occurring in China including smoggy weather and sand dust storm are threatening people's health and daily life [44,45]. An increasingly prominent energy crisis is realized by more and more entrepreneurs, politicians and academics [46].

Current environmental conditions may attract experts' attention on environmental, economic, social and technological aspects when they make judgments on DSM performances.

There were some uncertainties in decision-making processes when sub-criteria weights were determined by fuzzy AHP. Different experts may give different judgments, according to which the weights will vary. A sensitivity analysis about the sub-criteria weights should be performed to check the robustness and the effectiveness of the preference decision results. The fifteen sub-criteria were assigned into four groups according to main criteria, namely economic, social, environmental and technical group. The closeness coefficient values calculated by Equation (30) were regarded as the ranking scores of alternatives.

For performing the sensitivity analysis, the sub-criteria weights were increased by 20%, 40%, 60% and 80% and reduced by 20%, 40%, 60% and 80% compared with the basic weights (namely the global weights shown in Table 10). Let W_i be the basic weight of sub-criterion i, δ be the weight variation coefficient, namely −80%, −60%, −40%, −20%, 0%, 20%, 40%, 60% and 80%. The adjusted weight W_i^* of sub-criterion i is:

$$W_i^* = W_i \times (1 + \delta) \quad (31)$$

As the sum of all sub-criteria weights is set at 1, the rest are sequentially adjusted

$$W_j^* = W_j \times (1 - W_i^*)/(1 - W_i) \quad (32)$$

where W_j is the basic weight of sub-criterion j; W_j^* is the adjusted weight of sub-criterion j; and i, $j = 1, \ldots, 15$, $i \neq j$.

It is seen that the weight changes of the five sub-criteria in the economic group exert influences on the final ranking scores in Figure 9. It is shown that the DSM performance scores of all four alternative remain relatively stable with the weight changes of C2, C4 and C5. As the importance of C1 raises, the ranking scores of alternative O1 and O2 increase. Meanwhile, the ranking score of O4 (the best alternative) decreases slightly. As C3 becomes more and more important, the ranking scores of O3 and O4 (the best alternative) decrease obviously, while the ranking scores of O1 and O2 increase. However, no matter how the weights of C1 and C3 change, O4 still obtains the highest score and is regarded as the best one. In the case, no matter how the weights of sub-criteria in the economic group change, O4 still gets the highest ranking scores and that indicates O4 is always the best.

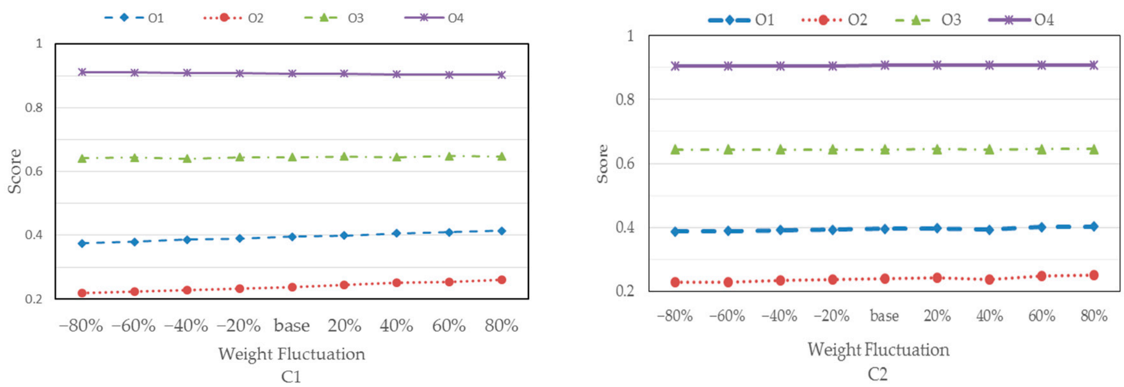

Figure 9. *Cont.*

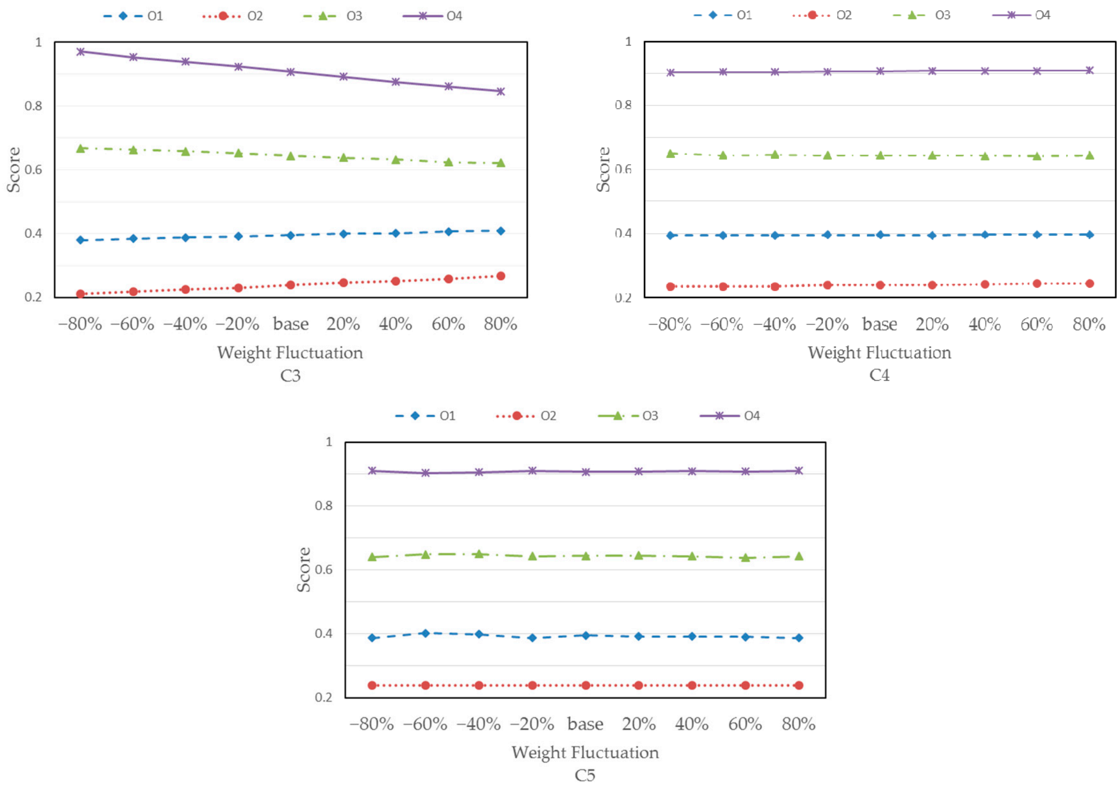

Figure 9. The sensitivity analysis result of the economic group.

The cases in which four sub-criteria affiliated to the social group have weight fluctuations are presented in Figure 10. No matter how the weights change, the ranking scores of all four alternatives barely change. O4 still ranks the first, while the others remain stable, no matter how the weights of the sub-criteria change in the social group.

The cases in which the weights of three sub-criteria fluctuate in the environmental group are shown in Figure 11. For C10, C11 and C12, as the weight increases, the score of O1 has little change, the scores of O3 and O4 increase, and score of O2 declines. However, the rankings of all alternatives remain unchanged. O4 is still the optimal alternative no matter how the weights of the sub-criteria in the environmental group fluctuate.

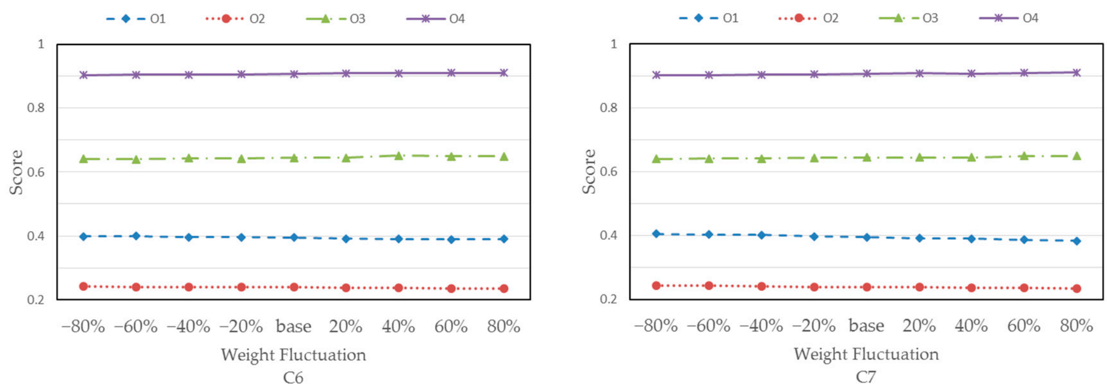

Figure 10. *Cont.*

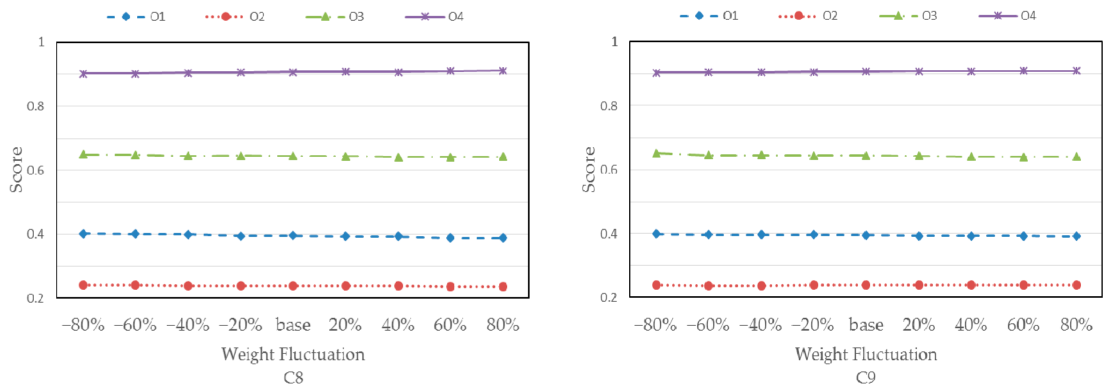

Figure 10. The sensitivity analysis result of the society group.

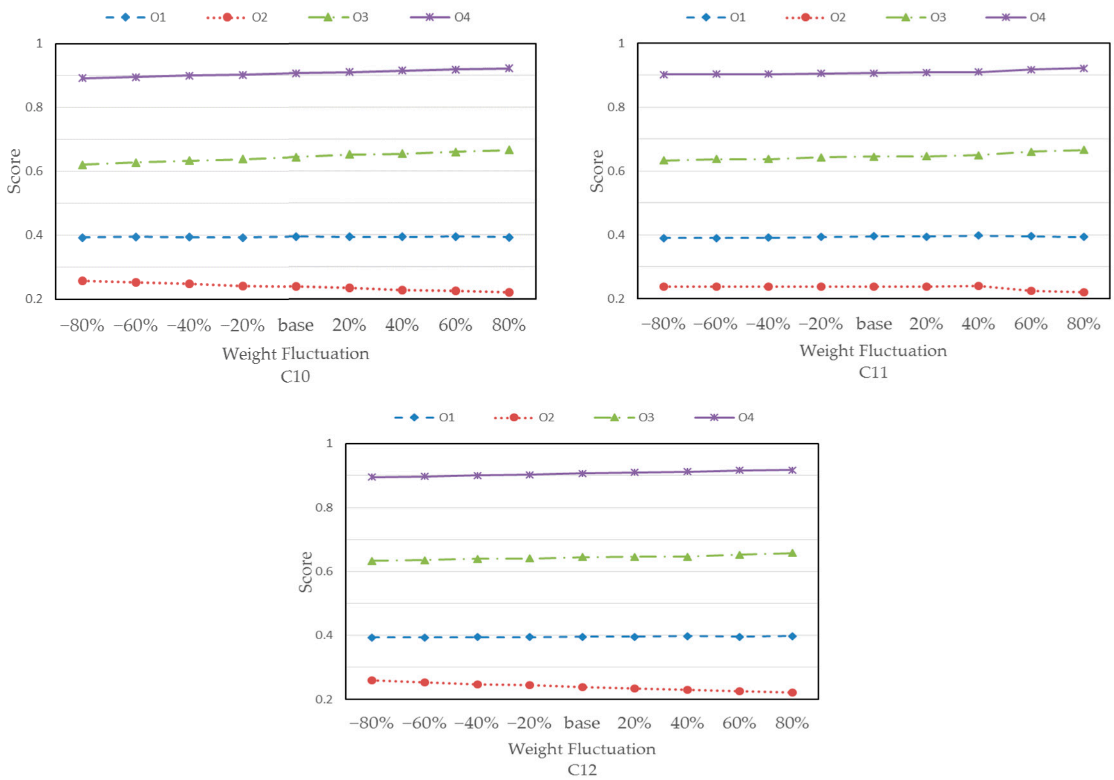

Figure 11. The sensitivity analysis result of the environment group.

The cases in which the weights of three sub-criteria fluctuate in the technical group are shown in Figure 12. As the weight of C13 increases, the ranking score of O4 increases slightly, while the score of O2 decreases. As the weight of C14 increases, the ranking score of O4 increases slightly and its superiority becomes greater, while the score of O1 decreases. For the weight fluctuations of C15, the scores of all alternatives have little variations. Just as that in the economic, social and environmental groups, O4 is still the optimal alternative no matter how the three sub-criteria weights change in the technical group.

Base on the above analysis, it is seen that O4 always obtains the highest score among all alternatives, which indicates that the DSM performance evaluation framework by applying the fuzzy AHP-TOPSIS approach is reliable and robust.

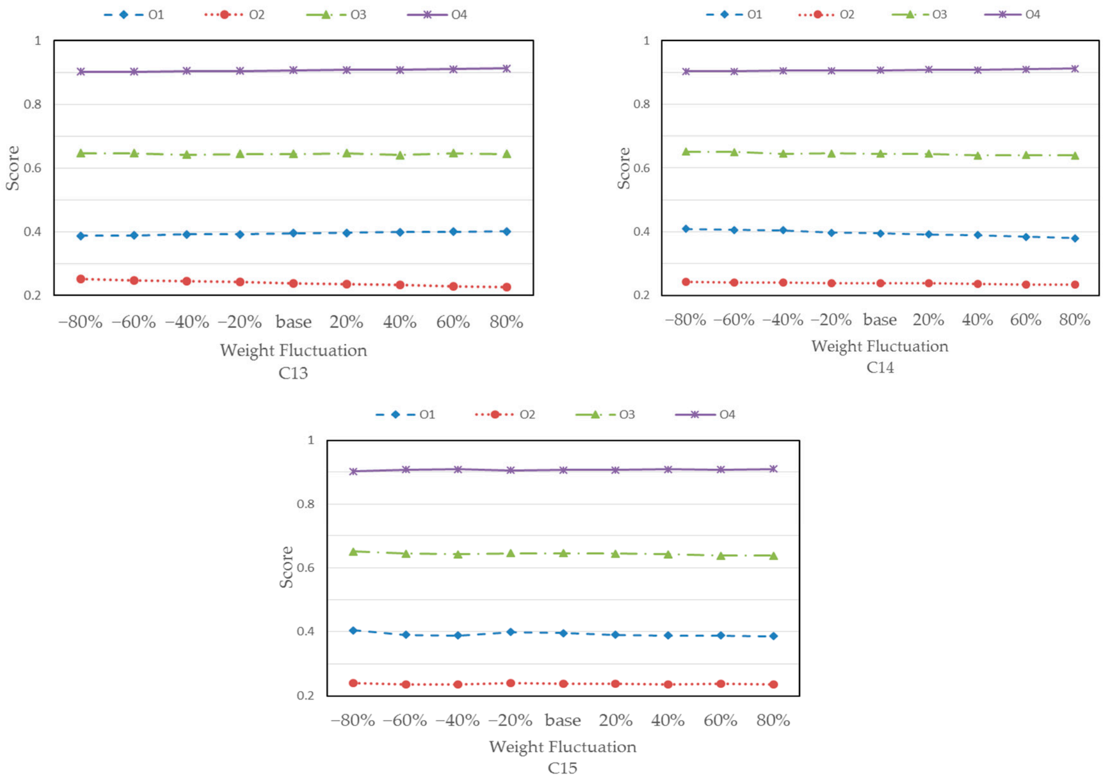

Figure 12. The sensitivity analysis result of the technical group.

6. Conclusions

The hybrid framework for the DSM performance evaluation in the commercial sector was built from a sustainability perspective, which was proven feasible and effective in the empirical analysis. Some conclusions has been drawn:

(1) It is found that C10 and C12 affiliated with the environment criteria obtain more attention from experts, and alternative O4 was chosen as the best, followed by O3, O1 and O2;

(2) A sensitivity analysis for the sub-criteria weights were performed to test the robustness and effectiveness of evaluation results, which indicated that the ranking results remain stable no matter how the weights of the sub-criteria change.

Although this hybrid framework is reasonable, robust and practical to evaluate and rank DSM performance, limitations may still appear with the changes of objective conditions. Considering the complexity and variability of such practical problems, other MCDM methods such as fuzzy VIKOR, fuzzy ANP or fuzzy PROMETHEE to rank the DSM performance should be used in future research. Meanwhile, the ranking results obtained from different MCDM methods can also be compared to improve the evaluation framework. Moreover, the evaluation index system can be improved by consulting more specific experts from fields related to the environment, the economy, and so on. The sub-criteria should be updated timely with changes of government policies and economic situations.

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