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Optimized PROMETHEE Based on Interval Neutrosophic Sets for New Energy Storage Alternative Selection

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Abstract
New energy storage alternative selection is a hot research issue that involves multiple-criteria decision-making process. In view of the existing deficiencies of multiple-criteria decision-making methods, an optimized method of PROMETHEE was proposed based on interval neutrosophic sets that has the advantage in describing fuzzy decision-making information. Robustness evaluation was conducted to verify the stability of the optimized method in comparison with other typical classical multiple-criteria decision-making methods. Experimental results show that the optimized method can solve the existing problems such as unavoidable subjectivity, information uncertainties and compensation between indicators with more reasonable results. Finally, an empirical study was performed to verify the effectiveness of this optimized method in order to provide a reference for dynamic- group decision-making in new energy storage alternative selections.

Key words: New Energy Storage Alternative Selection, Multiple-criteria Decision-making, Optimized PROMETHEE Method, Interval Neutrosophic Set

1. INTRODUCTION

The new energy storage technology is one of the indispensable supporting technologies in smart grid, renewable energy access, distributed generation, micro-grid system and electric vehicle. It is the strong support for demand-side management. Meanwhile, it can eliminate peak-valley difference, smooth load, improve the operating efficiency of electrical equipment, reduce power supply costs, help the system to restart and recover quickly after the catastrophic accident and improve the system's self-healing ability. The Peak-valley difference continues to increase along with the quick expansion of grid capacity in the 21stcentury, moreover the distributed energy supply and smart grid are developing rapidly and the demands for new energy storage are also growing. However, the sophisticated environment of power system determines that single technology cannot meet with multiple demands simultaneously. In practice, different energy storage technologies are integrated for the greatest advantages in order to improve flexibility and technical economy for energy storage system. In a new energy storage project, energy storage alternative selection is the most crucial and vital step. Reasonable and effective results are required to make the project more scientific and efficient. Based on the fact that the energy storage alternative selection can be abstract as multiple-criteria decision-making (MCDM) process, it is required to be optimized both in the process and the results as the influencing factors are complex and interrelated. ES-Select, an energy storage selection software developed by Sandia National Lab was used on energy storage rough selection under numerous uncertain factors due to the consideration of different working conditions in energy system and characteristics of energy storage technologies(Sandia National Laboratories, 2012), however, in the scoring stage, the subjective influence was raised by the simplified classification process. Pham et.al (Pham, 2015)used fuzzy logic as a selection method after compare the results of the multi-criteria analysis with the present experience and literature of energy storage applications, Barin et. al (Barin, 2009)proposed a methodology taking as basis of the AHP (analytic hierarchy process) and fuzzy logic which evaluates the operation of storage energy systems to develop a multi-criteria analysis to find the appropriate storage energy system concerning a power quality scenario, yet problems still exist: firstly, information duplication exists during the evaluation process; secondly, the weight of each factor is determined by a certain group of experts hence the subjectivity is inevitable; finally, under certain circumstances, the determination of the membership function is difficult. In particular, for MCDM, the process is cumbersome. Al-Nory et.al (Al-Nory, 2015) proposed a mathematical model based on linear programming which allows the evaluation of various storage systems and different types of batteries from economic and performance aspects, however linear programming method requires high accuracy of data and massive calculation, moreover, only linear problems can be programmed which can be considered as a big limitation because many problems are non-linear. Li et. al (Li, 2016) applied IAHP to process uncertainty and fuzzy problems when information is incomplete, it is noteworthy that in the entire process the decision makers are actively involved in it, therefore, the IAHP method is practical for decision-makers, indicating that the subjectivity is not only inevitable, but also, in many cases, be too strong since one of the requirements of new energy storage alternative selection is to avoid subjectivity to the greatest extent.

As can be seen from the above, although these MCDM methods provided effective research methodology for new energy storage alternative selection, there are still deficiencies (Vucijak, 2013): firstly, subjectivity cannot be avoided indecision-making and information uncertainties in the selection process will lead to risks; secondly, decision-making information is fuzzy and compensation between the indicators exist in the selection system; thirdly, the above-mentioned methods require massive calculation. According to the characteristics of new energy storage alternative selections, following requirements are demanded for MCDM methods: firstly, the impact of subjectivity should be minimized; secondly, as energy storage projects have characteristics of time-varying, dynamic-decisions are required; thirdly, the imperfectness of decision-making information should be taken into consideration; finally, the computational complexity should be minimized for better application in practice.

In this paper, a new selection method is presented by using optimized PROMETHEE based on interval neutrosophic sets to make up for the gap of traditional methods, the stability is verified by the robustness evaluation, and then the empirical study is performed to validate the feasibility and effectiveness of the optimized method in order to provide a reference for new energy storage alternative selections.

2. OPTIMIZED PROMETHEEBASED ONINTERVAL NEUTROSOPHIC SETS

2.1.Advantages of Interval Neutrosophic Set

Traditional fuzzy sets focus only on membership degree yet the non-membership degree is neglected. Although the later proposed intuitionistic fuzzy sets and the interval intuitionistic fuzzy sets had added non-membership degrees to the fuzzy sets, they can only process incomplete informationwhilethe uncertain and inconsistent information are beyond the ability. In order to comprehensively process all kinds of information, Smarandache (Smarandache, 1999) proposed the neutrosophic number theory which focus on the hesitancy degree that intuitionistic fuzzy number had neglected, in comparison with intuitionistic fuzzy number, the neutrosophic number is more suitable for processing uncertain information. However, the single-valued neutrosophic sets use real numbers to represent the membership degree, non-membership degree and hesitancy degree which cannot better represent the ambiguity of information. Wang et. al(Wang, 2005)put forward the interval neutrosophic sets with interval number to represent the membership degree, non-membership degree and hesitancy degree in order to get more reliable results.

Up to the present, many multi-attribute decision-making methods have emerged, such as TOPISIS, VIKOR, ELECTRE, Gray Correlation Degree, Grey Projection, etc. yet neither the real number nor the fuzzy numberis as good as the interval neutrosophic number in describing the fuzzy decision-making information. Therefore, in this article, we take interval neutrosophic set as a basis to better deal with the problems which traditional MCDM methods have in new energy storage alternative selection.

2.2.Definition of Interval Neutrosophic Set

Suppose that X was a non-empty set and x was an element of X set, then $A=\{T_A(x),I_A(x),F_A(x)|x\in X\}$ was called a neutrosophic set of X, where $T_A(x)$, $I_A(x)$ and $F_A(x)$ represented membership, hesitancy and non-membership respectively and $T_A(x)$, $I_A(x)$ and $F_A(x)$ belonged to $]0^-,1^+[$, $0^-\le T_A(x)+I_A(x)+F_A(x)\le 3^+$.

Suppose that X was a non-empty set and x was an element of X set, then an interval neutrosophic set of X can be expressed as $A=\{T_A(x),I_A(x),F_A(x)|x\in X\}$, where $T_A(x)$, $I_A(x)$ and $F_A(x)$ represented membership, hesitancy and non-membership respectively and $T_A(x)$, $I_A(x)$ and $F_A(x)$ belonged to $[0,1]$, $0\le \sup(T_A(x))+\sup(I_A(x))+\sup(F_A(x))\le 3$ (Govindan,2015).

Suppose that $x=([T_x^L,T_x^U],[I_x^L,I_x^U],[T_x^L,T_x^U])$ and $y=([T_y^L,T_y^U],[I_y^L,I_y^U],[T_y^L,T_y^U])$ were two interval neutrosophic sets, then we had the following operational rules(Samanlioglu,2016):

(1) $x\oplus y=([T_x^L+T_y^L-T_x^LT_y^L,T_x^U+T_y^U-T_x^UT_y^U],[I_x^LI_y^L,I_x^UI_y^U],[F_x^LF_y^L,F_x^UF_y^U])$

(2) $x\otimes y=\begin{pmatrix}[T_x^LT_y^L,T_x^UT_y^U],[I_x^L+I_y^L-I_x^LI_y^L,I_x^L+I_y^L-I_x^LI_y^L],\\ [F_x^L+F_y^L-F_x^LF_y^L,F_x^U+F_y^U-F_x^UF_y^U]\end{pmatrix}$

(3) $nx=([1-(1-T_x^L)^n,1-(1-T_x^U)^n],[(T_x^L)^n,(T_x^L)^n],[(F_x^L)^n,(F_x^L)^n])\ n>0$

2.3.Decision-making Process of the Optimized PROMETHEE Based on Interval Neutrosophic Sets

We combine interval neutrosophic sets with PROMETHEE to overcome the difficulties in processing complex, fuzzy and uncertain information in decision-making in order to get better application in practice. Specific process is as follows:

(1) Collect group opinions

Suppose that there were s experts in the group and the weight of the k th expert was ξ_k. The score that this expert gave to Alternative A_i in terms of Criterion C_j was $\tilde{n}_{ij}^k = ([T_{ij}^L(\tilde{n}_k)\ ,\ T_{ij}^U(\tilde{n}_k)]\ ,[I_{ij}^L(\tilde{n}_k)\ ,\ I_{ij}^U(\tilde{n}_k)]\ ,[F_{ij}^L(\tilde{n}_k)\ ,\ F_{ij}^U(\tilde{n}_k)])$, $k=1,2,...,s$, $i=1,2,...,m$, $j=1,2,...,n$ .After scores given by s experts were collected, an expert group opinion matrix N was obtained by using a generalized weighted average operator (INULGWA) of interval neutrosophic sets. The element N_{ij} in the matrix was calculated as follows:

$$\begin{aligned}\tilde{N}_{ij} = INULGWA(\tilde{n}_{ij}^1,\tilde{n}_{ij}^2,...,\tilde{n}_{ij}^s) = ([(1-\prod_{k=1}^{s}(1-T_{ij}^L(\tilde{n}_k)^\lambda)^{\xi_k})^{1/\lambda},(1-\prod_{k=1}^{s}(1-T_{ij}^U(\tilde{n}_k)^\lambda)^{\xi_k})^{1/\lambda}],\\ [1-(1-\prod_{k=1}^{s}(1-(1-I_{ij}^L(\tilde{n}_k))^\lambda)^{\xi_k})^{1/\lambda},1-(1-\prod_{k=1}^{s}(1-(1-I_{ij}^U(\tilde{n}_k))^\lambda)^{\xi_k})^{1/\lambda}],\\ [1-(1-\prod_{k=1}^{s}(1-(1-F_{ij}^L(\tilde{n}_k))^\lambda)^{\xi_k})^{1/\lambda},1-(1-\prod_{k=1}^{s}(1-(1-F_{ij}^U(\tilde{n}_k))^\lambda)^{\xi_k})^{1/\lambda}])\end{aligned} \quad (1)$$

Based on the expert group opinions collection, an expert group decision-making (EGDM) matrix was built:

$$N_{m\times n} = \begin{bmatrix} N_{11} & N_{12} & ... & N_{1n} \\ N_{21} & N_{22} & ... & N_{2n} \\ ... & ... & ... & \vdots \\ N_{m1} & N_{m2} & ... & N_{mn} \end{bmatrix} \quad (2)$$

(2) Build priority function based on possibility

To evaluate the priority of alternatives, this article firstly made a comparison between alternatives in terms of various criteria. To build a reasonable comparison, we introduced the definition of possibility.

Suppose that $\tilde{N}_{ij} = ([T_{ij}^L,T_{ij}^U],[I_{ij}^L,I_{ij}^U],[F_{ij}^L,F_{ij}^U])$ and $\tilde{N}_{i'j} = ([T_{i'j}^L,T_{i'j}^U],[I_{i'j}^L,I_{i'j}^U],[F_{i'j}^L,F_{i'j}^U])$ were interval neutrosophic scores of alternatives A_i and $A_{i'}$ in terms of Criterion C_j. $i=1,2,...,m$, $i \neq i'$, $j=1,2,...,n$. Then a comparison of possibility between $\tilde{N}_{ij}$ and $\tilde{N}_{i'j}$ was:

$$P(\tilde{N}_{ij} \geq \tilde{N}_{i'j}) = \frac{1}{3}\left\{P([T_{ij}^L,T_{ij}^U] \geq [T_{i'j}^L,T_{i'j}^U]) + P([I_{ij}^L,I_{ij}^U] \geq [I_{i'j}^L,I_{i'j}^U]) + P([F_{ij}^L,F_{ij}^U] \geq [F_{i'j}^L,F_{i'j}^U])\right\} \quad (3)$$

Where $P([T_{ij}^L,T_{ij}^U] \geq [T_{i'j}^L,T_{i'j}^U]) = \max\{1-\max(\frac{T_{i'j}^U - T_{ij}^L}{T_{ij}^U - T_{ij}^L + T_{i'j}^U - T_{i'j}^L},0),0\}$;

Likewise, $P([I_{ij}^L,I_{ij}^U] \geq [I_{i'j}^L,I_{i'j}^U])$, $P([F_{ij}^L,F_{ij}^U] \geq [F_{i'j}^L,F_{i'j}^U])$.

Suppose that p and q were strictly prior to threshold and non-differential threshold respectively. Based on a comparison of possibility between neutrosophic sets N_{ij} and $N_{i'j}$, a priority function $y(N_{ij},N_{i'j})$ in terms of Criterion C_j was built:

$$y(\tilde{N}_{ij},\tilde{N}_{i'j}) = \begin{cases} 1\ \ ,P(N_{ij} \geq N_{i'j}) - 0.5 > p \\ (\left|P(N_{ij} \geq N_{i'j}) - 0.5\right| - q)/(p-q), q < P(N_{ij} \geq N_{i'j}) - 0.5 \leq p \\ 0\ \ ,P(N_{ij} \geq N_{i'j}) - 0.5 \leq q \end{cases} \quad (4)$$

The priority function $y(N_{ij},N_{i'j})$ represented the priority degree of Score N_{ij} to Score $N_{i'j}$. When $y(N_{ij},N_{i'j})$ was equal to 1, it meant that Score N_{ij} of Alternative A_i was prior to Score $N_{i'j}$ of Alternative $A_{i'}$ in terms of Criterion C_j . $y(N_{ij},N_{i'j}) \sim 0.5$ meant that N_{ij} was weakly prior to $N_{i'j}$. $y(N_{ij},N_{i'j}) \sim 0$ meant that N_{ij} was inferior to $N_{i'j}$, or there was no difference between them.

(3) Build weighted priority function

Suppose that the criterion set C had differential weight information. The weight of element C_j was w_j. The priority function between Alternative A_i and Alternative $A_{i'}$ in terms of Criterion C_j was $y(N_{ij}, N_{i'j})$. $w_j = ([\varpi_j^L, \varpi_j^U],[\omega_j^L, \omega_j^U],[\upsilon_j^L, \upsilon_j^U])$. $i = 1,2,...,m$, $i \neq i'$, $j = 1,2,...,n$. Weighted priority function can be built as follows:

$$\begin{aligned} Z_{ii'} = \quad & ([1-\prod_k^l (1-\varpi_j^L)^{y(N_{ij},N_{i'j})}, 1-\prod_k^l (1-\varpi_j^U)^{y(N_{ij},N_{i'j})}],[\prod_k^l (\omega_j^L)^{y(N_{ij},N_{i'j})}, \prod_k^l (\omega_j^U)^{y(N_{ij},N_{i'j})}], \\ & [\prod_k^l (\upsilon_j^L)^{y(N_{ij},N_{i'j})}, \prod_k^l (\upsilon_j^L)^{y(N_{ij},N_{i'j})}]). \end{aligned} \tag{5}$$

Based on the weighted priority function, alternative comparison matrix was built as follows:

$$Z_{m\times m} = \begin{bmatrix} - & Z_{12} & \cdots & Z_{1m} \\ Z_{21} & - & \cdots & Z_{2m} \\ \cdots & \cdots & \cdots & \vdots \\ Z_{m1} & Z_{m2} & \cdots & - \end{bmatrix} \tag{6}$$

According to the alternative comparison matrix, inflow function $\tilde{\varphi}^-(\tilde{A}_i)$ and an outflow function $\tilde{\varphi}^+(\tilde{A}_i)$ were built:

$$\tilde{\varphi}^+(\tilde{A}_i) = \frac{1}{m-1} \overset{m}{\underset{i'=1,i\neq i'}{\oplus}} Z_{ii'} \tag{7}$$

$$\tilde{\varphi}^-(\tilde{A}_i) = \frac{1}{m-1} \overset{m}{\underset{i'=1,i\neq i'}{\oplus}} Z_{i'i} \tag{8}$$

The formulas of inflow and outflow functions showed that the higher value of $\tilde{\varphi}^+(\tilde{A}_i)$, the higher possibility that Alternative A_i was prior to other alternatives. The higher value of $\tilde{\varphi}^-(\tilde{A}_i)$, the higher possibility that other alternatives were prior to Alternative A_i. According to the inflow and outflow functions, a binary comparison between alternatives was built:

I. $A_i \succ A_{i'}$, when $\tilde{\varphi}^+(\tilde{A}_i) \succ \tilde{\varphi}^+(\tilde{A}_{i'})$ and $\tilde{\varphi}^-(\tilde{A}_i) \succ \tilde{\varphi}^-(\tilde{A}_{i'})$, or $\tilde{\varphi}^+(\tilde{A}_i) \succ \tilde{\varphi}^+(\tilde{A}_{i'})$ and $\tilde{\varphi}^-(\tilde{A}_i) = \tilde{\varphi}^-(\tilde{A}_{i'})$; or $\tilde{\varphi}^+(\tilde{A}_i) = \tilde{\varphi}^+(\tilde{A}_{i'})$ and $\tilde{\varphi}^-(\tilde{A}_i) \prec \tilde{\varphi}^-(\tilde{A}_{i'})$.

II. $A_i = A_{i'}$, when $\tilde{\varphi}^-(\tilde{A}_i) = \tilde{\varphi}^-(\tilde{A}_{i'})$ and $\tilde{\varphi}^+(\tilde{A}_i) = \tilde{\varphi}^+(\tilde{A}_{i'})$.

III. In other cases, A_i and A_i were incomparable.

IV. Based on the binary comparison between alternatives, the final ranking between alternatives can be obtained.

3. ROBUSTNESS EVALUATION OF OPTIMIZED PROMETHEE METHOD

3.1.Indicators of Robustness Evaluation

In order to verify the stability of the optimized PROMETHEE method, The Monte Carlo Simulation was used to compare the robustness of the optimized PROMETHEE method based on interval neutrosophic sets with typical classical MCDM methods. Evaluation indicators include: optimal alternative consistency, alternative sorting rate, mean square error and mean absolute deviation.

(1) For a method of h, after K-times' simulation, the optimal alternative consistency was:

$$S^{Top\_h} = \frac{1}{k}\sum_k S_k^{Top\_h} \tag{9}$$

The value of S^{Top_h} represents the consistency of k^{th} (k=1,2,…,K) simulation with reference value, whichwas presented as follows:

$$S_k^{Top\_h} = \begin{cases} 1, \text{Optimal alternative is consistent with the reference value} \\ 2, \text{Optimal alternative is not consistent with the reference value} \end{cases}$$

(2) alternative sorting rate was:

$$S^{Rank\_h} = \frac{1}{K}\sum_k \frac{1}{n}\left(\sum_i S_{ki}^{Rank\_h}\right) \quad (10)$$

$S_{ki}^{Rank\_h}$ is the k^{th} simulation which represent whether the sorting of alternative i is consistent with the baseline value, whichwas presented as follows:

$$S_{ki}^{Rank\_h} = \begin{cases} 1, \text{Alternative with the rank i is consistent with the reference value} \\ 0, \text{Alternative with the rank i is not consistent with the reference value} \end{cases}$$

(3) The mean square error S^{Variance_h} was:

$$S^{\text{Variance}\_h} = \frac{1}{K}\sum_k \sqrt{\sum_i \left(S_{ki}^{\text{Variance}\_h} - S_{ki}^{\text{Variance}\_Benchmark}\right)^2} \quad (11)$$

Where $S_{ki}^{\text{Variance}\_h}$ is the k^{th} simulation that represents the ordinal number of Alternative i $S_{ki}^{\text{Variance}\_Benchmark}$ is the k^{th} simulation which represent the ordinal number of reference value.

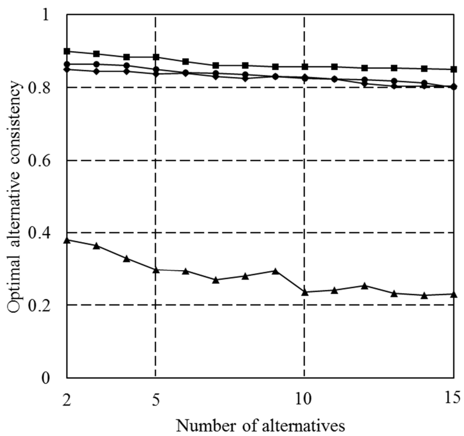
(4) Mean Absolute Deviation S^{Mean_h} was:

$$S^{Mean\_h} = \frac{1}{K}\sum_k \sum_i \left|S_{ki} - S_{ki}^{Mean\_Benchmark}\right| \quad (12)$$

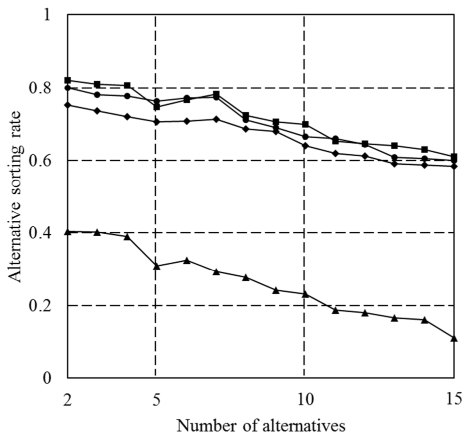
3.2The Robustness Evaluation Process

We chose several typical classical MCDM methods include TOPSIS, PROMETHEE, ELECTRE-III to compare with the optimized PROMETHEE based on interval neutrosophic sets and AHP as a benchmark for robustness comparison due to its strong stability and wide range of applications. The evaluation process included comparison of robustness when the number of alternatives and indicators change respectively.

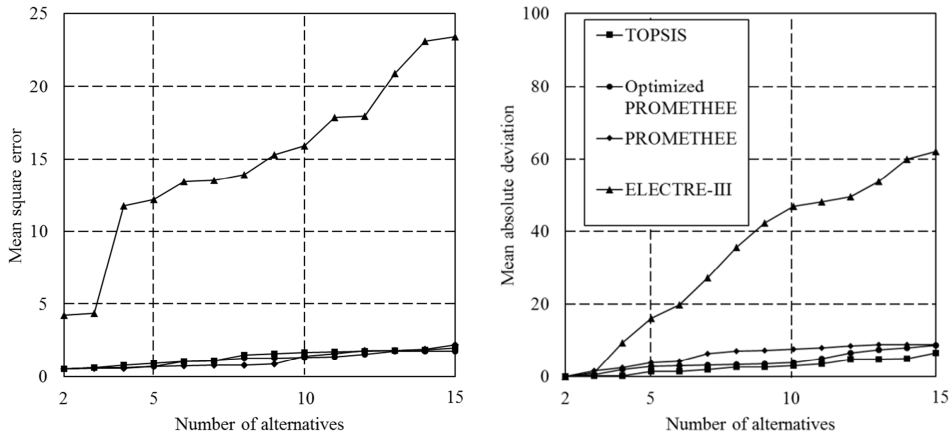
Comparison of robustness when the number of alternatives change. The average weight was taken when the number of alternatives changed from 2 to 15, compare each method with AHP and the optimal alternative consistency S^{Top_h}, alternative sorting rate S^{Rank_h}, mean square error S^{Variance_h} ,and mean absolute deviation S^{Mean_h} were shown in Figure1.As shown in Figure 1, S^{Top_h} and S^{Rank_h} were presenting downward trends; S^{Variance_h}, S^{Mean_h} were presenting upward trends, indicating that the robustness of each method decreases with the increasing number of alternatives; according to the data, the robustness of TOPSIS, PROMETHEE and optimized PROMETHEE were similar with each other and significantly stronger than ELECTRE-III; the robustness of optimized PROMETHEE was between TOPSIS and PROMETHEE and was slightly stronger than PROMETHEE.



(a) Optimal alternative consistency



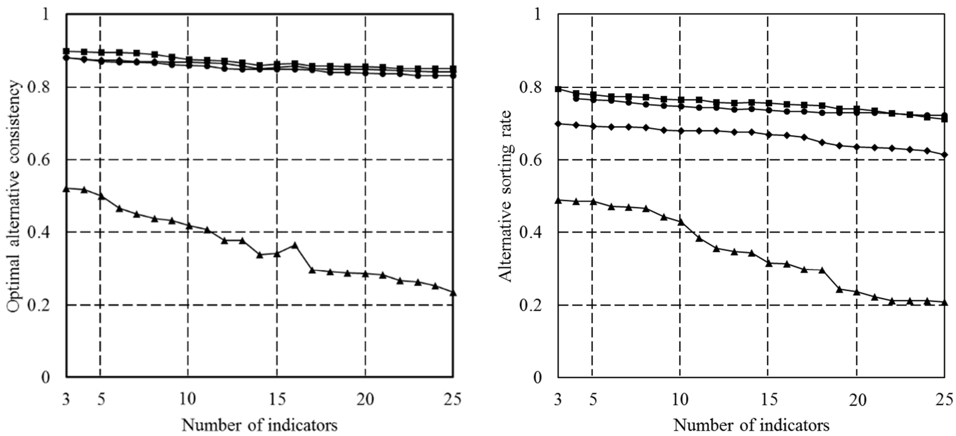
(b) Alternative sorting rate



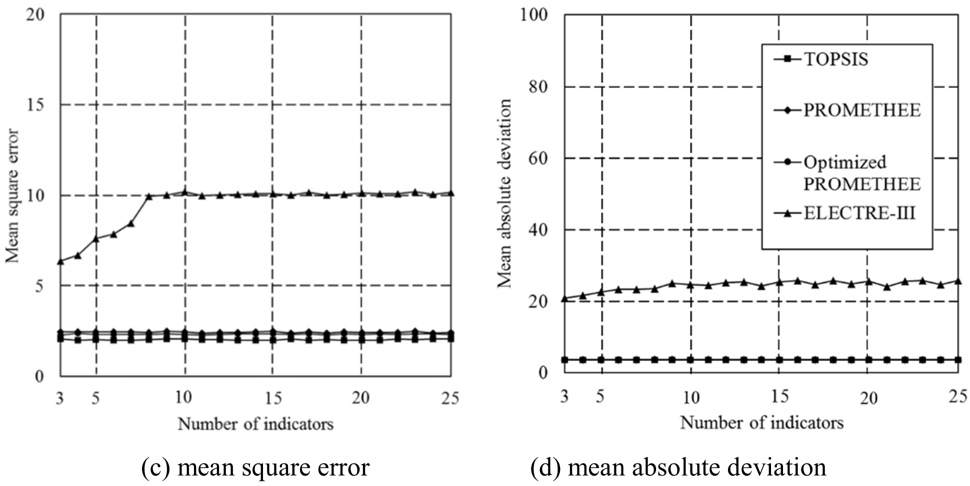
(c) Mean square error (d) Mean absolute deviation

Figure 1. Comparison of Robustness When the Number of Alternative Change

Comparison of robustness when the number of indicators change. Average weight was taken for each method to compare with AHP when the number of indicators changed from 3 to 25. S^{Top_h}, S^{Rank_h}, S^{Variance_h} and S^{Mean_h} were shown in Figure 2.



(a) optimal alternative consistency (b) alternative sorting rate



(c) mean square error (d) mean absolute deviation

Figure 2. Comparison of Robustness When the Number of Indicators Change

As shown in Figure 2, S^{Top_h} and S^{Rank_h} were presenting downward trends S^{Variance_h}, S^{Mean_h} were presenting upward trends, indicating that the robustness of each method decreased with the increasing number of indicators; according to the data, the robustness of TOPSIS, PROMETHEE and optimized PROMETHEE were similar with each other and significantly stronger than ELECTRE-III; the robustness of optimized PROMETHEE was between TOPSIS and PROMETHEE and is slightly stronger than PROMETHEE.

The ELECTRE-III, PROMETHEE and optimized PROMETHEE are relation model based on outranking relation while the TOPSIS is technique for order preference by similarity to an ideal solution. As can be seen from Figure 1 and Figure 2, TOPSIS, PROMETHEE and optimized PROMETHEE were showing strong robustness, and the robustness of ELECTRE-III was weak; TOPSIS had the strongest robustness, however this method relies on non-dimensional processing and will lead to distortion or loss of information; both of the optimized PROMETHEE and traditional PROMETHEE had the adaptability and flexibility to the environment, and the robustness of optimized PROMETHEE was slightly stronger than traditional PROMETHEE both when the number of the alternatives and indicators change, indicating that optimized PROMETHEE had good applicability for new energy storage alternative selection.

4. EMPIRICAL STUDY

Four solution sets from a new energy demonstration project in Inner Mongolia, China were selected as the alternative sets. A comprehensive indicator system which involves aspects of economy, technology, security and scale, etc. was constructed. Indicators are shown in Figure 3.

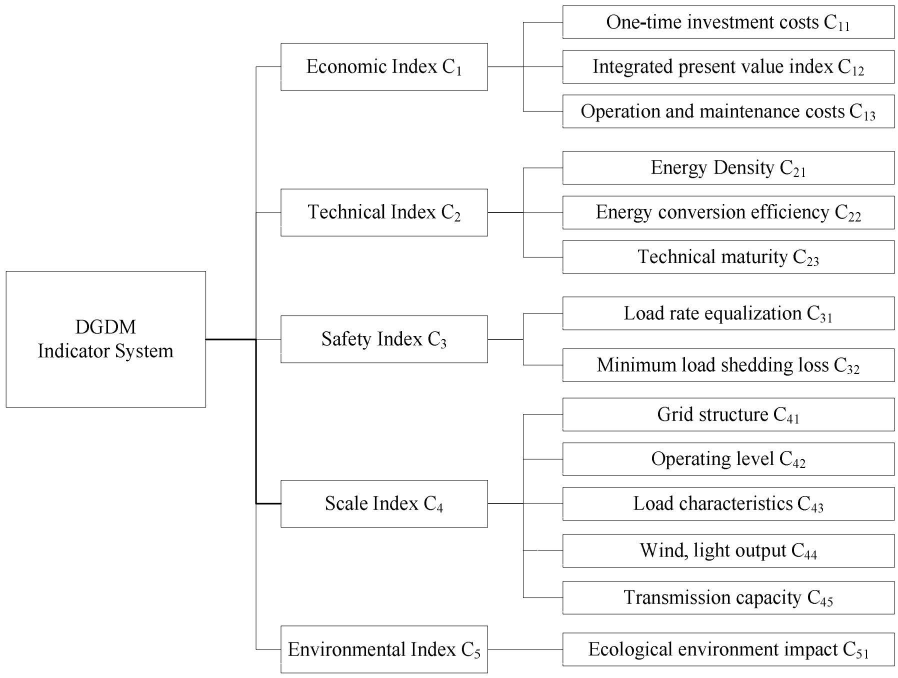


Figure 3. The DGDM Indicator System for New Energy Storage Alternative Selection

Decision-making process and results of optimized PROMETHEE based on interval neutrosophic sets were shown as follows:

(1)Build the EGDM matrix

In this stage, a decision-making group composed of five experts scored each indicator of each alternative respectively and then formed an expert opinionaire. Meanwhile, to ensure independent scoring, Delphi method was adopted. After four rounds of scoring and feedback, expert opinions tended to be stable. On this basis, the generalized weighted average operator (Formula (1)) of interval neutrosophic sets was used, expert opinions were gathered and an EGDM matrix was built, as shown in Table 1.

Table 1. Gathering Expert Group Opinions

Alternative	C_{11}	C_{12}	C_{13}
A_1	([0.6,1],[0.1,0.2],[0.1,0.2])	([0.3,0.9],[0.2,0.3],[0.2,0.3])	([0.4,0.9],[0.2,0.3],[0.2,0.3])
A_2	([0.8,1],[0,0.1],[0,0.1])	([0.8,1],[0.1,0.1],[0.1,0.1])	([0.8,1],[0.1,0.1],[0.1,0.1])
A_3	([0.8,1],[0,0.1],[0,0.1])	([0.8,1],[0,0.1],[0,0.1])	([0.8,1],[0,0.1],[0,0.1])
A_4	([0.8,1],[0.1,0.1],[0.1,0.1])	([0.8,1],[0,0.1],[0,0.1])	([0.8,1],[0,0.1],[0,0.1])
	C_{21}	C_{22}	C_{23}
A_1	([0.6,1],[0.1,0.2],[0.1,0.2])	([0.6,1],[0.1,0.2],[0.2,0.3])	([0.6,1],[0.1,0.2],[0.1,0.2])
A_2	([0.5,1],[0.2,0.3],[0.1,0.2])	([0.6,1],[0.1,0.2],[0.1,0.2])	([0.6,1],[0.1,0.2],[0.1,0.2])
A_3	([0.6,1],[0.1,0.2],[0.1,0.2])	([0.6,1],[0.1,0.2],[0.1,0.2])	([0.4,0.9],[0.2,0.3],[0.2,0.2])

A_4	([0.8,1],[0,0.1],[0.1,0.2])	([0.4,0.9],[0.2,0.3],[0.2,0.3])	([0.8,1],[0,0.1],[0,0.1])
	C_{31}	C_{32}	C_{41}
A_1	([0.8,1],[0,0.1],[0.1,0.2])	([0.4,0.9],[0.2,0.3],[0.2,0.3])	([0.8,1],[0,0.1],[0,0.1])
A_2	([0.5,1],[0.2,0.2],[0.1,0.2])	([0.8,1],[0.1,0.1],[0.1,0.1])	([0.3,0.9],[0.2,0.3],[0.2,0.3])
A_3	([0.4,0.9],[0.2,0.3],[0.2,0.2])	([0.4,0.9],[0.2,0.3],[0.1,0.2])	([0.8,1],[0,0.1],[0,0.1])
A_4	([0.4,0.9],[0.2,0.3],[0.2,0.3])	([0.6,1],[0.1,0.2],[0.1,0.2])	([0.7,1],[0.1,0.2],[0.1,0.2])
	C_{42}	C_{43}	C_{44}
A_1	([0.3,0.9],[0.2,0.3],[0.2,0.3])	([0.4,0.9],[0.2,0.3],[0.2,0.3])	([0.7,1],[0.1,0.2],[0.1,0.2])
A_2	([0.8,1],[0,0.1],[0,0.1])	([0.4,0.9],[0.2,0.3],[0.2,0.2])	([0.6,1],[0.1,0.2],[0.1,0.2])
A_3	([0.3,0.9],[0.2,0.3],[0.2,0.3])	([0.4,0.9],[0.2,0.3],[0.2,0.3])	([0.6,1],[0.1,0.2],[0.1,0.2])
A_4	([0.6,1],[0.1,0.2],[0.1,0.2])	([0.4,0.9],[0.2,0.3],[0.2,0.3])	([0.7,1],[0.1,0.1],[0.1,0.2])
	C_{45}	C_{51}	
A_1	([0.8,1],[0.1,0.1],[0.1,0.1])	([0.8,1],[0,0.1],[0,0.1])	
A_2	([0.9,1],[0,0.1],[0,0.1])	([0.6,1],[0.1,0.2],[0.1,0.2])	
A_3	([0.8,1],[0.1,0.1],[0.1,0.1])	([0.4,0.9],[0.2,0.3],[0.2,0.3])	
A_4	([0.8,1],[0,0.1],[0,0.1])	([0.4,0.9],[0.2,0.3],[0.2,0.2])	

(2) Calculate weighted priority function

Step 1: Calculate the priority function. On the basis of EGDM matrix, a comparison of possibility between alternatives in different indicators was calculated by using Formula (3). After experts discussion, the values of p and q were identified as $p = 0.05$ and $q = 0.5$ respectively. Then, the priority function was calculated using Formula (4).

Step 2: Calculate the weight of indicators. The expert group scored weights of different indicators independently. After 4 rounds of scoring and feedback, the scoring of experts tended to be stable. On this basis, weight information given by each expert was gathered by using INULGWA operator to form indicator weight group decision-making matrix.

Step 3: Calculate the weighted priority function. After getting priority function and indicator weights, a priority comparison matrix was built by using the weighted priority function calculated in Formula (5). The results are shown in Table 2.

Table 2. The Priority Comparison Matrix

	A_1	A_2	A_3	A_4
A_1	-	([0.9532,0.9994], [0.0000,0.0001], [0.0000,0.0012])	([0.8157,0.9823], [0.0000,0.0091], [0.0028,0.0296])	([0.9495,0.9992], [0.0000,0.0002], [0.0000,0.0016])
A_2	([0.6537,0.9220], [0.0011,0.0430], [0.0222,0.0942])	-	([0.7035,0.9443], [0.0004,0.0326], [0.0149,0.0762])	([0.7622,0.9663], [0.0002,0.0229], [0.0092,0.0585])
A_3	([0.5966,0.8905], [0.0024,0.0607], [0.0339,0.1222])	([0.9252,0.9981], [0.0000,0.0006], [0.0001,0.0038])	-	([0.8410,0.9882], [0.0000,0.0047], [0.0013,0.018])
A_4	([0.6850,0.9361], [0.0009,0.0396], [0.0204,0.0881])	([0.9296,0.9983], [0.0000,0.0005], [0.0001,0.0032])	([0.6847,0.9345], [0.0008,0.0415], [0.0205,0.0913])	-

Step 4: Calculate the inflow and outflow functions. Based on the alternative comparison matrix, by using Formulas (7) and (8), the inflow and outflow functions of each alternative were calculated. The results are shown in Table 3.

Step 5: Build a binary comparison between alternatives. Based on the inflow and outflow comparing principle, the ranking was obtained, that is, $A_2 \succ A_4 \succ A_3 \succ A_1$, indicating that in this case, the alternative A_2 was the priority selected by using optimized PROMETHEE method.

Table 3. Inflow and Outflow Functions

	A_1	A_2	A_3	$\mathbf{A_4}$
Inflow	([0.9044,0.9964], [0.0000,0.0011], [0.0002,0.0035])	([0.6435,0.9134], [0.0017,0.0585], [0.0307,0.0786])	([0.8181,0.9837], [0.0000,0.0069], [0.0022,0.0241])	([0.7562,0.9659], [0.0001,0.0180], [0.0073,0.0338])
outflow	([0.6885,0.9396], [0.0006,0.0321], [0.0156,0.0756])	([0.9505,0.9993], [0.0000,0.0001], [0.0000,0.0014])	([0.7718,0.9702], [0.0001,0.0157], [0.0059,0.0443])	([0.8885,0.9948], [0.0000,0.0019], [0.0004,0.0091])

5. CONCLUSION

This article firstly combined interval neutrosophic set theory with PROMETHEE method to build a new optimized selection method for new energy storage alternative selections to deal with existing deficiencies that traditional MCDM methods have such as unavoidable subjectivity, information uncertainties and compensation between indicators more effectively. By taking advantages of interval neutrosophic sets in presenting results and PROMETHEE method in strong practicability, it provided a feasible solution for uncertain decision information in the process of new energy storage alternative selection.

Robustness evaluation was made to verify stability of currently wildly used typical classical MCDM methods, including TOPSIS, PROMETHEE, ELECTRE-III and optimized PROMETHEE based on interval neutrosophic sets to compare with AHP. Optimal alternative consistency, alternative sorting rate, mean square error and mean absolute deviation were calculated under the conditions of number change in alternatives and indicators respectively. Results showed strong stability of optimized PROMETHEE based on interval neutrosophic sets, and compared to other methods, it didn’t rely on non-dimensional processing which will lead to distortion or loss of information, indicating that this method has strong practicality in new energy storage alternative selection.

Finally, an empirical study of a new energy demonstration project in Inner Mongolia, China was conducted to validate the feasibility and effectiveness of the new method. It can be seen from the study that the optimized PROMETHEE based on interval neutrosophic sets can not only do well with the information uncertainties and compensation between indicators, but also can simplify the calculation process. This optimized method was proved to have practicality and furthermore provide a reference for the new energy storage alternative selections.

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