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Sustainability Prioritization of Energy Systems under Hybrid Information and Missing Information based on the Improved Grey Relational Analysis

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ABSTRACT: Life cycle sustainability of energy systems has received more and more attentions recently. In order to make an accurate comparison of the sustainability performance of different energy systems and promote the decision-making process, various prioritization methods of energy systems were developed. However, the lack of enough data for decision-making usually limits the accuracy of the prioritization. On the one hand, the decision-makers can only collect multiple types of data resources with hybrid information, for example, data in the formats of crisp numbers, interval numbers, and fuzzy numbers. On the other hand, some information for certain alternatives with respect to certain criteria is hard to be obtained. Therefore, it is of vital importance to achieve sustainability-oriented prioritization of energy systems under hybrid information and missing information. This study aims at developing a prioritization framework for energy systems ranking with missing information and hybrid information. An improved Grey Relational Analysis (GRA) is extended from the classical GRA method to handle hybrid information in this study. An innovative method to quantify linguistic expressions is proposed to deal with missing information. A hypothetical case study regarding electricity generation scenarios selection was used to evaluate the feasibility of this proposed framework. Sensitivity analysis was also conducted, and the results showed that the iGRA-MH is feasible in handling hybrid and missing information and it performs more stable than other multi-criteria decision-making models.

KEYWORDS: Sustainability; Multi-criteria Decision Making; Grey Relational Analysis; Hybrid information; Multi-criteria Decision Making; Life cycle sustainability

List of Acronyms

iGRA-MH	Improved Grey Relational Analysis for Missing and Hybrid information
LCA	Life cycle assessment
LCSA	Life cycle sustainability assessment
LCC	Life cycle costing
S-LCA	Social life cycle assessment
MCDM	Multi-criteria decision-making
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
GRA	Grey Relational Analysis
VIKOR	Vlse kriterijumska optimizacija kompromisno resenje
PROMETHEE	Preference ranking organization method for enrichment evaluations
MULTIMOORA	Multi-objective optimization on the basis of ratio analysis with the full multiplicative form
BWM	Best-Worst Method
AHP	Analytical Hierarchy Process
DEMATEL	Decision Making Trial and Evaluation Laboratory

List of Symbols

$\hat{a}_{ij}$	The performance of the *i*-th alternative on the *j*-th criterion
a	A crisp number
a^l	The lower boundary of an interval number
a^u	The upper boundary of an interval number
a^L	The lower boundary of a triangle fuzzy number
a^M	The most possible value of a triangle fuzzy number
a^U	The upper boundary of a triangle fuzzy number
c_i	The *j*-th criterion
e_{ij}	The preference of criterion *i* over the worst criterion *j*
w_j	The weight of criterion *j*
w_j^*	The optimal weight of criteria *j*
ξ^*	The minimum error
x_{ij}	The element of the *i*-th row and the *j*-th column of normalized decision-making matrix *X*
x_j^+	The *j*-th element of the ideal criterion vector X^+
γ_{ij}	The grey relational coefficient of the *i*-th alternative regarding the *j*-th criterion
Δ_{ij}	The distance of the *j*-th criterion with regard to the *i*-th alternative to that of the ideal option
ζ	Distinguishing coefficient
$\Delta_{\min}$	The minimum value of criteria differences
$\Delta_{\max}$	The maximum value of criteria differences
Γ_i	The grey relational grade of the *i*-th alternative

1. Introduction

The supply of energy is essential to maintain the operations of the modern city. Energy supply not only contributes to necessity supply for mankind, such as food supply, product manufacturing, operations of electrical devices and vehicles, but also is strongly related to national security and is the basis for the development of science and technology [1–3]. Therefore, a long-term and stable supply of energy is very important.

In order to measure the stability and development potential of energy supply, sustainability has been applied as an effective index for the measurement of energy systems. The concept of sustainability has been proposed for years, and it has become relatively mature and accepted. In addition to environmental concerns, sustainability can also consider economic, social, technological, and other aspects. The concept of sustainability is in line with the long-term supply needs of the energy system. Therefore, it is of great significance to evaluate the sustainability of the energy system. Life cycle assessment (LCA) is one of the well-admitted environmental sustainability assessment tools, and it has been used to analyse the environmental performance of energy systems in previous studies. Welfle *et al.*[4] conducted LCA for several bioenergy scenarios. Mehmeti *et al.*[5] examined the environmental sustainability of hydrogen production methods via LCA. The LCA of coal-fired power generation in China was conducted [6]. Since sustainability of energy systems can be addressed in more than environmental aspects, life cycle sustainability assessment (LCSA) including LCA, life cycle costing (LCC), and social life cycle assessment (S-LCA), was usually used for sustainability assessment. Atilgan and Azapagic[7] studied the sustainability of the electricity generation system in Turkey. Patel *et al.*[8] reviewed the techno-economic and lifecycle assessment on lignocellulosic biomass thermochemical conversion technologies. The LCSA has also been adopted to assess the sustainability of grid-connected photovoltaic power generation in Northeast England [9]. Kabayo *et al.*[10] assessed LCSA of key electricity generation systems in Portugal. These studies provided quantitative results of the sustainability of energy systems.

Now that energy systems are diversified, the selection of energy systems has also become an important decision-making issue. Since each energy system has its own advantages and disadvantages, the multi-criteria decision-making (MCDM) method becomes an effective decision-making tool that can help decision-makers to prioritize or select the most suitable options from more than one candidate based on multiple criteria. Multi-criteria Decision Making (MCDM) can be used to select the most sustainable one among multiple alternatives, for example, Yadav *et al*.[11] analysed the adoption of effective offshore outsourcing using the ELECTRE method. A classical MCDM method, Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method, was used to select the solar form site [12]. Zhang *et al.*[13] conducted a water consumption evaluation based on grey relational analysis (GRA).

To prioritize technologies in the energy systems based on sustainability, the study of multi-attribute decision-making based on the sustainability of energy systems has effectively solved some comparative problems of energy systems. Ren *et al.*[14]

proposed a framework coupling the LCSA and MCDM method to prioritize electricity generation scenarios. Lin *et al.*[15] also developed a novel MCDM method and constructed a similar framework that combined with LCSA to prioritize the biorefinery systems according to their sustainability performances.

MCDM methods aiming at sustainability analysis have been extended to deal with uncertainties in order to solve more complicated problems. For instance, distributed energy system has been analysed by using interval VIKOR [16]. Tabaraee *et al.*[17] prioritize power plants by using the fuzzy PROMETHEE method. An improved fuzzy MULTIMOORA approach was proposed to select the technological forecasting method [18]. Some extended MCDM methods were also proposed to solve various situations in other fields. For instance, Mathew *et al.*[19] studied a novel MCDM method based on AHP and TOPSIS to select advanced manufacturing systems. A supplier selection problem was studied based on fuzzy TOPSIS [20]. However, prioritization decision-making of energy systems often needs to face the problem with hybrid information. This situation is often caused by data aggregation from diverse data sources, difficulties in prioritizing the alternatives when the data for decision-making are from different sources or in different formats. Some MCDM methods to deal with hybrid types of data are proposed based on classical MCDM methods. For example, The VIKOR method was improved to deal with crisp, random and hesitant fuzzy numbers[21]. The TOPSIS method was extended to deal with hybrid information [22,23]. But the existing energy system prioritization methods based MCDM rarely consider the decision-making under hybrid information.

In addition, the limitations in data collection may also lead to missing information or incomplete information. The missing information is usually solved by using linguistic expressions. Those linguistic terms with level grading are transformed to numerical numbers by using intuitionistic fuzzy numbers [24,25]. However, the experts may express their own preference by comparative degree. For example, the technology maturity of pumped storage is recognized as "the best" among all energy storage technologies, and the fuel cost of wind power is "lower than" nuclear power. Both "the best" and "lower than" are linguistic terms and they should be transformed into numerical values. But the quantification of these types of linguistic terms cannot be solved in existing MCDM methods. Therefore, the transformation of comparative linguistic terms to numerical values is another important problem to be solved in this prioritization framework.

In this study, a generic framework for life cycle sustainability prioritization of energy systems under hybrid information and missing information is proposed to provide a more reliable and accurate analysis for sustainability performance assessment. This study could fill in the following two research gaps:

1) Energy systems prioritization based on a decision-making matrix under hybrid information.
2) Energy systems prioritization based on a decision-making matrix with missing information.

The rest of this study is recognized as below. The sustainability prioritization framework of energy systems to deal with hybrid information and missing information is proposed in section 2. An illustrative case study regarding electricity generation pathways selection is studied in section 3. In section 4, the result of the case study is presented and discussed. This study is concluded in session 5.

2. Methodology

This study aims at proposing a new life cycle sustainability prioritization framework for the energy system to handle the decision-making problem with hybrid information and missing information. In this framework, the criteria system for sustainability prioritization of energy systems is built up based on LCSA. Then, the Best-Worst Method (BWM) [26] is used to determine the weights of criteria and GRA [27] is extended to Improved Grey Relational Analysis for Missing and Hybrid information (iGRA-MH) to handle hybrid information and missing information. BWM model is a weight calculation method proposed by Rezeai in 2015. Comparing with some traditional weighting methods, especially the AHP method, the BWM requires only the comparison calculations between the best alternative (criterion) and the others, and between the others to the worst alternative (criterion). Therefore, BWM is recognized as an effective method to determine the weights of the criteria. GRA is a classical method to show the similarity between two systems. It was used for MCDM as it can show the relativeness of the target system and ideal system. The concept of comparison is more suitable in this situation since the treatment of hybrid information is based on the reference points. The GRA has been proven feasible and efficient for decision-making in many studies. However, the traditional GRA cannot be used to prioritize the energy systems based on the decision-making matrix with hybrid information or missing information. Therefore, the extension of GRA is prerequisite to ensure the accuracy of the result. The combination of BWM and GRA models helps to accurately prioritize the alternatives with fewer steps. The generic framework of life cycle sustainability prioritization of energy systems under hybrid information is shown in **Fig.1**.

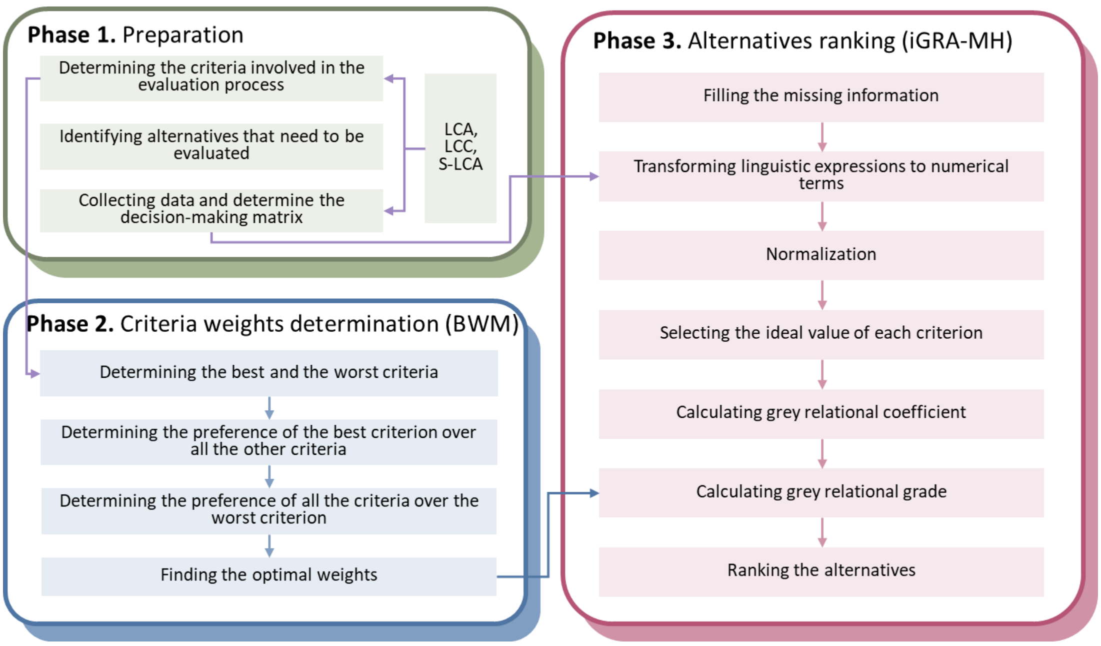


Figure 1. The multi-criteria decision making framework for energy system prioritization

To clarify the calculation and evaluation processes, we define three hybrid types of information in this study accordingly.

- **Type I Hybrid Information:** the data with respect to the same criterion are the same data type.
- **Type II Hybrid Information:** the data of the same alternative are the same data

type.

- **Type III Hybrid Information:** the data with respect to any criterion or the data of any alternative are different data types.

The examples of Type I, II, and III Hybrid Information are presented in **Tables 1-3**.

Table 1. Example of Type I Hybrid Information

Criteria	Unit	T1	T2	T3	T4
Removal rate	%	[60,80]	[50,70]	[50,80]	[60,70]
Land use	km^2	Medium	High	Very high	Very low
Investment capital	RMB m^{-3}	1900	2000	2200	3600

Table 2. Example of Type II Hybrid Information

Criteria	Unit	T1	T2	T3	T4
Removal rate	%	The highest	[50,70]	60	[60,66,70]
Land use	km^2	Medium	[4500,6000]	8000	[6500,7000,7500]
Investment capital	RMB m^{-3}	Low	[2000,2400]	2200	[3000,3600,4000]

Table 3. Example of Type III Hybrid Information

Criteria	Unit	T1	T2	T3	T4
Removal rate	%	The highest	[50,70]	60	Relatively high
Land use	km^2	3,000	[4500,6000]	8000	Very low
Investment capital	RMB m^{-3}	[1900,2000,2400]	[2000,2400]	Medium	3600

The accuracy of the methods related to different hybrid types will be discussed and analysed in section 4.

Assume that m alternatives are prioritized based on n criteria regarding life cycle sustainability, then the decision-making matrix can be presented in **Eq.(1)**.

$$A = \begin{bmatrix} \hat{a}_{11} & \hat{a}_{12} & \cdots & \hat{a}_{1n} \\ \hat{a}_{21} & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ \hat{a}_{m1} & \cdots & \cdots & \hat{a}_{mn} \end{bmatrix} \tag{1}$$

where $\hat{a}_{ij}$ represents the performance of the i-th alternative on the j-th criterion, and it might be any of the information types as shown in **Fig.2** and **Table 4**.

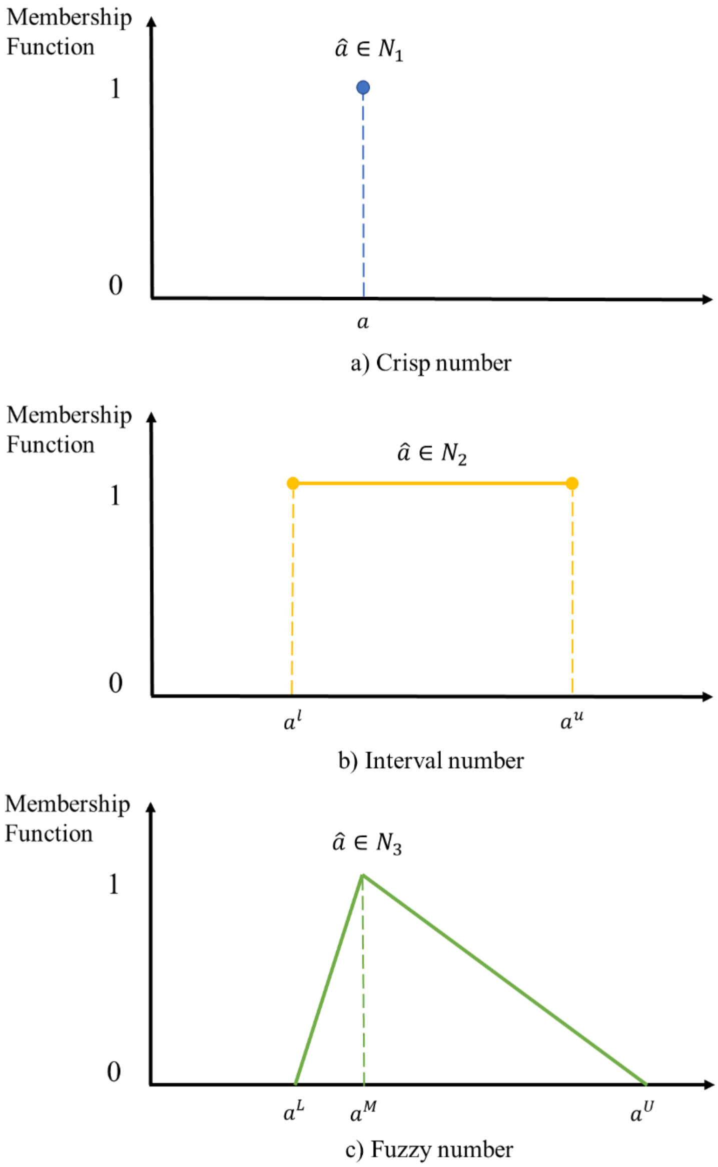


Figure 2. Types of hybrid information

Table 4. Information types and numerical expressions

Value set	Information type	Numerical expression	
N_1	Crisp number	a	$if\ \hat{a} \in N_1$
N_2	Interval number	(a^l, a^u)	$if\ \hat{a} \in N_2$
N_3	Triangle fuzzy number	(a^L, a^M, a^U)	$if\ \hat{a} \in N_3$
N_4	Linguistic terms	Should be transformed into interval numbers or	$if\ \hat{a} \in N_4$

	triangle fuzzy numbers

Based on the above preliminaries, the prioritization framework of energy systems is specified as follows.

2.1 Criteria system

To assess the life-cycle performances of energy systems, a multiple-aspect criteria system should be created for an overall evaluation. In a criteria system for LCSA, criteria in economic, environmental, and social aspects are usually included. The criteria and the data with respect to the criteria are usually obtained and selected from LCSA. LCSA is an integrated lifecycle sustainability assessment, which is consists of LCA for environmental assessment, LCC for economic assessment and S-LCA for social analysis. These assessments quantify the performance of each alternative in environmental, economic and social aspects with united criteria. To be specific, the criteria in environmental, economic, and social aspects are selected from attributes in LCA, LCC, and S-LCA, respectively. The criteria to describe the environmental performance of alternatives include global warming, greenhouse gas emission, water eutrophication, land occupation, and so on. The economic criteria usually consist of criteria related to the costs and economic benefits of this system, such as capital cost, operation cost, maintenance cost, net profit, and rate of return. As for social criteria, employment, human health, and social benefits are usually considered. The criteria are presented in **Fig. 3**.

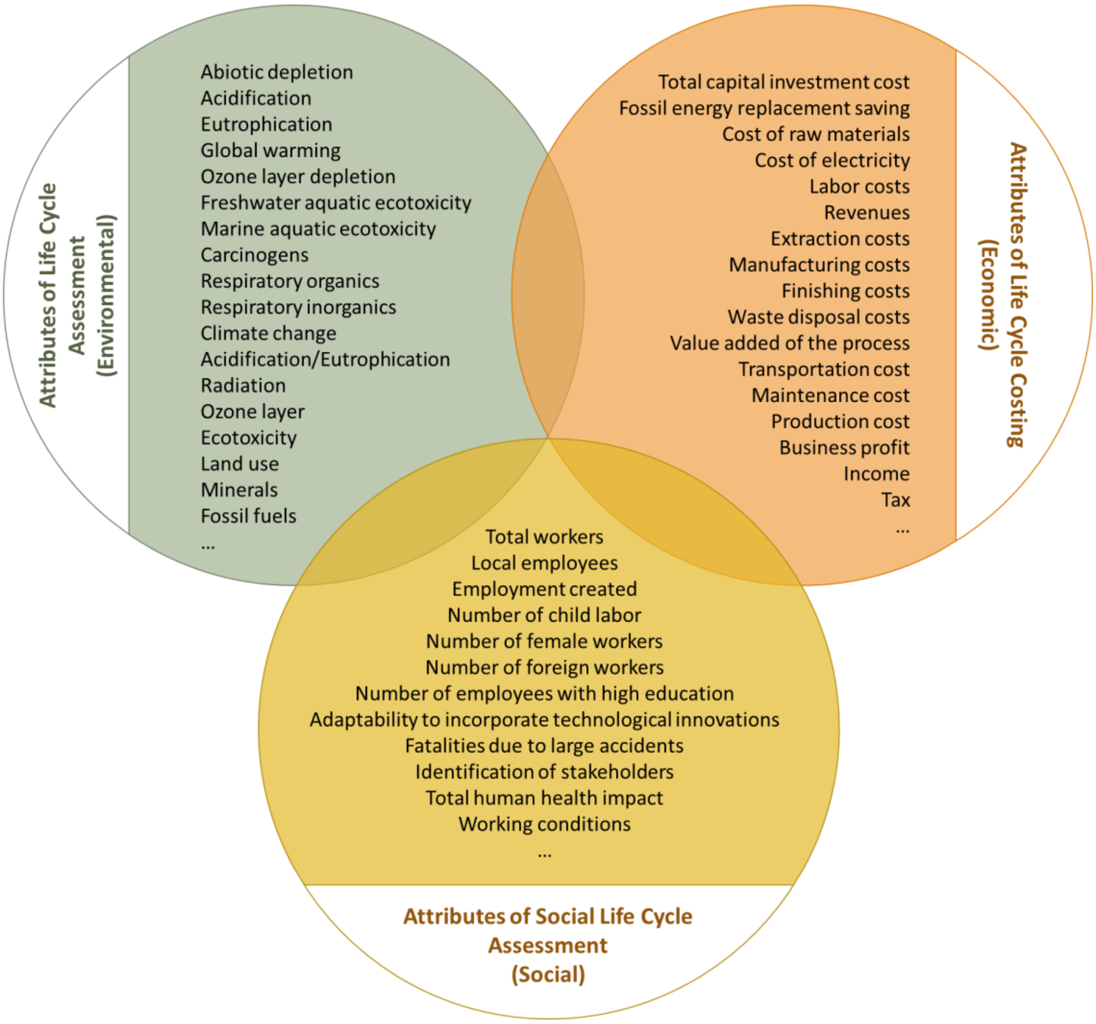


Figure 3 Criteria system based on Life Cycle Sustainability Assessment (Adapted from [28])

The selection of criteria should follow basic rules (Adapted from [15]):

- No overlapping in the criteria system. When more than one criterion of the same meaning is selected for evaluation, the decision maker needs to determine which one is most suitable.
- The criteria system should sufficiently describe the overall performance. To be specific, at least one criterion should be selected for each aspect.

Since the situation of certain systems and the preference of decision makers will differ in each case, the criteria should be selected and decided by decision makers accordingly. The data with respect to the criteria can be obtained through corresponding life cycle assessments.

2.2 Determination of criteria weights - Best Worst Method (BWM)

Since different decision makers hold different opinions in different cases, the weights of criteria should be determined in the prioritization framework. There are several methods that have been used to determine the weights of criteria, such as Analytical Hierarchy Process (AHP)[29], DEMATEL[30], entropy weighting method[31], and Fuzzy Delphi method[32]. In this study, the BWM [26] is used since BWM adapted the concept of pairwise comparison and can calculate criteria weights with fewer steps comparing with the AHP method. The calculation process developed by Rezaei[26, 33] was specified as follows:

Step 1. Determining a set of decision criteria. Based on the criteria selected in the criteria system, the decision criteria could be summarized as a set of decision criteria written as $C = (c_1, c_2, \ldots, c_n)$.

Step 2. Determining the best and the worst criteria. According to the judgment of decision-makers, the most important criterion and the less important criterion are selected as the best criterion (c_B) and the worst criterion (c_W), respectively.

Step 3. Determining the preference of the best criterion over all the other criteria using a number between 1 and 9. The resulting Best-to-Others vector is shown as **Eq.(2)**.

$$E_B = (e_{B1}, e_{B2}, \ldots, e_{Bn}) \quad (2)$$

where e_{Bj} indicates the preference of the best criterion B over criterion j. Assume that there are 4 criteria among which the 2nd criterion is the best, then the Best-to-Others vector could be expressed as **Table 5**.

Table 5. Example of Best-to-Others vector

	c_1	c_2	c_3	c_4
c_2	e_{B1}	e_{BB}	e_{B3}	e_{BW}

Step 4. Determining the preference of all the criteria over the worst criterion using a number between 1 and 9. The resulting Others-to-Worst vector is presented in **Eq.(3)**.

$$E_W = (e_{1W}, e_{2W}, \ldots, e_{nW})^T \quad (3)$$

where e_{jW} indicates the preference of criterion j over the worst criterion W. Assume that there are 4 criteria among which the 4th criterion is the worst, then the Others-to-Worst vector can be expressed as **Table 6**.

Table 6. Example of Others-to-Worst vector

	c_4
c_1	e_{1W}
c_2	e_{BW}
c_3	e_{3W}
c_4	e_{WW}

Step 5. Finding the optimal weights. The weights regarding the j-th criterion, the best

criterion, and the worst criterion can be written as w_j, w_B and w_W respectively. The optimal weights can be determined by solving **Eq.(4)**.

$$
\begin{aligned}
& \min \xi \\
& s.t. \\
& \left| \frac{w_B}{w_j} - e_{Bj} \right| \leq \xi, \text{for all } j \\
& \left| \frac{w_j}{w_w} - e_{jW} \right| \leq \xi, \text{for all } j \\
& \sum_j w_j = 1 \\
& w_j \geq 0, \text{for all } j
\end{aligned}
\tag{4}
$$

The solution $(w_1^*, w_2^*, \ldots, w_n^*)$ indicates the optimal criteria weights and the minimum error ξ^* can be obtained when the equation is satisfied with the optimal solution. The optimal solution should be validated through consistency index calculation. The consistency ratio (CR) of BWM can be determined by **Eq.(5)**.

$$\text{Consistency Ratio} = \frac{\xi^*}{\text{Consistency Index}} \tag{5}$$

where consistency index (CI) can be referred to **Table 7**.

Table 7. Consistency index table [26]

e_{BW}	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Consistency index	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

If CR<0.1, the result passes the consistency test. The smaller the value of CR, the more consistent the result is. If CR≥ 0.1, the result fails the consistency test, and the Best-to-Others vector and the Others-to-Worst vector should be revised and repeat steps 3-5 until the requirement is satisfied.

2.3 Alternatives ranking

2.3.1 Grey relational analysis

The GRA was originally proposed by Deng [34] as an important part of grey system theory. In this theory, grey, a colour between black and white, is applied to indicate uncertain information and the degree of grey reflects the degree of certainty The GRA can assist in calculating the grey relational coefficient which is a significant basis for decision making.

Assume that there are *m* alternatives and *n* criteria in this analysis. The value of the *i*-th alternative with regards to the *j*-th criterion is written as $\hat{a}_{ij}$ as shown in **Eq.(1)**. The $\hat{a}_{ij}$ could be any data types as shown in **Table 4**. In this method, all inputs are crisp numbers. In another word, $\hat{a}_{ij} \in N_1$ for all $i \in (1,2,\ldots m)$ and $j \in (1,2,\ldots,n)$ in GRA, and all $\hat{a}_{ij}$ can be simplified as a_{ij}. The calculation process of the original version of GRA were specified in the following four steps [27,35,36]:

Step 1. Normalization. Noted that the units of the criteria are different, and it is impossible to compare the alternatives with respect to different criteria with different units. In addition, the criteria can be classified as benefit-type criteria and cost-type criteria. A benefit-type criterion means that the higher value is better. On the contrary, a cost-type criterion means that the lower value is more preferred. In order to make all the criteria dimensionless, the element x_{ij} of the *i*-th row and the *j*-th column of normalized decision-making matrix *X* can be determined by **Eqs.(6)-(7)**.

$$x_{ij} = \frac{a_{ij} - \min_i a_{ij}}{\max_i a_{ij} - \min_i a_{ij}} \quad i = 1,2,\ldots,m, j \in B \tag{6}$$

$$x_{ij} = \frac{\max_i a_{ij} - a_{ij}}{\max_i a_{ij} - \min_i a_{ij}} \quad i = 1,2,\ldots,m, j \in C \tag{7}$$

where *B* indicates the benefit-type criteria, and C represents the cost-type criteria.

Step 2. Choosing ideal criterion value. An ideal alternative with all ideal criteria values is constructed as a reference for sustainability performance judgment. The *j*-th element x_j^+ of the ideal criterion vector X^+ can be determined by **Eq.(8)**.

$$x_j^+ = \max_i x_{ij} \quad j = 1,2,\ldots,n \tag{8}$$

Step 3. Calculating the grey relational coefficient. The grey relational coefficient γ_{ij} of the *i*-th alternative regarding the *j*-th criterion can be determined by **Eq.(9)**.

$$\gamma_{ij} = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{ij} + \zeta \Delta_{\max}} \quad i = 1,2,\ldots,m, j = 1,2,\ldots,n \tag{9}$$

where Δ_{ij} represents the distance of the *j*-th criterion with regard to the *i*-th alternative to that of the ideal option and is determined by **Eq.(10)**. $\zeta \in [0,1]$is the distinguishing coefficient. $\Delta_{\min}$ and $\Delta_{\max}$ represent the minimum and maximum values of criteria differences, respectively, which are shown in **Eqs.(11)-(12)**.

$$\Delta_{ij} = x_{ij}^+ - x_{ij} \quad i = 1,2,\ldots,m, j = 1,2,\ldots,n \tag{10}$$

$$\Delta_{\min} = \min_i \min_j \Delta_{ij} \quad i = 1,2,\ldots,m, j = 1,2,\ldots,n \tag{11}$$

$$\Delta_{\max} = \max_i \max_j \Delta_{ij} \quad i = 1,2,\ldots,m, j = 1,2,\ldots,n \tag{12}$$

Step 4. Calculating grey relational grade. The grey relational grade Γ_i of the *i*-th alternative can be determined by **Eq.(13)**.

$$\Gamma_i = \sum_{j=1}^{n} w_j \gamma_{ij} \quad i = 1,2,\dots,m \tag{13}$$

The alternatives thereafter can be prioritized by ranking grey relational grades in descending orders.

2.3.2 Improved grey relational analysis (iGRA-MH)

An improved GRA is proposed which is extended based on the classic one to process hybrid information including crisp numbers, interval numbers, trapezoidal fuzzy numbers, and linguistic expressions. The missing information can be dealt with in the proposed approach, which is the so-called iGRA-MH method. The calculation process mainly includes six steps: i) filling the missing information; ii) transforming linguistic terms into numerical numbers; iii) normalization; iv) identifying the ideal value for each criterion; v) calculating the grey relational coefficient; and vi) calculating the grey relational grade. Similar to what is mentioned above, assume that there are *m* alternatives and *n* criteria in this analysis. The value of the *i*-th alternative with regards to the *j*-th criterion is written as $\hat{a}_{ij}$ as shown in **Eq.(1)**. The $\hat{a}_{ij}$ could be any data types as shown in **Table 4**.

Step 1. Filling the missing information

The situation of missing information occurs when numerical information of a certain alternative on a certain criterion cannot be obtained. To fill the missing information, a decision maker can describe the performance of this alternative regarding this criterion by using linguistic terms based on the knowledge of the experts or their own preferences. The frequently used linguistic expressions could be either level grading or comparative grading. As for level grading, the performance of certain alternatives with respect to certain criterion is judged without comparison. For example, the greenhouse gas emission of coal-based electricity generation can be determined as “poor”, and the electricity scale of nuclear electricity generation can be judged as “very good”. As for comparative grading, the performance of certain alternative with respect to certain criterion is expressed based on comparison with other alternatives with respect to this criterion. For instance, the technology maturity of pumped storage is “the best” among all energy storage technologies. The capital cost of one energy system is lower than that of another energy system.

To avoid the failure in transforming linguistic expressions to numerical terms, the following rules should be followed when handing the missing information:

1) There should not be such a set of criteria, with respect to whose values are determined and only determined by referring to the value with respect to other criteria in this set. If two or more criteria are the reference criteria for each other, the values of those criteria cannot be determined.

2) The data of at least one alternative with respect to each criterion is obtained, otherwise, the analysis cannot be conducted. If the requirement cannot be fulfilled,

which means no data is provided, this criterion is suggested to be removed from the criteria system.

Step 2. Transforming linguistic expressions to numerical terms

The linguistic term $(\hat{a}_{ij} \in N_4)$ needs to be transformed into the numerical expressions before adapted in the ranking calculation. Numerical terms transformation for level grading has been studied in some intuitionistic MCDM, such as fuzzy AHP[37] and fuzzy BWM[31]. The transformation approach is presented in **Table 8**.

Table 8. Numerical transformation for level-grading linguistic terms [25]

Linguistic term	**Numerical expression after normalization**
Very poor	(0, 0.1, 0.2)
Poor	(0.1, 0.2, 0.3)
Medium poor	(0.3, 0.4, 0.5)
Fair	(0.4, 0.5, 0.6)
Medium good	(0.5, 0.6, 0.7)
Good	(0.7, 0.8, 0.9)
Very good	(0.8, 0.9, 1)

The transformation for comparative grading is seldom mentioned in the MCDM studies. In this study, we proposed a transformation method for comparative linguistic terms. For the value of the i_0-th alternative with respect to the j_0-th criterion, the comparative linguistic terms can be transformed to numerical terms $\hat{a}_{i_0 j_0}$. The details of transformation are presented below.

- If this alternative is better than a set of alternatives $\boldsymbol{Q}$, the value of the alternative $\hat{a}_{i_0 j_0} = [a^l_{i_0 j_0}, a^u_{i_0 j_0}]$ can be determined by **Eqs.(14)-(15)**. The lower bound of $\hat{a}_{i_0 j_0}$ can be determined by the maximum value of alternatives in the set $\boldsymbol{Q}$ with respect to the j_0-th criterion. The upper bound of $\hat{a}_{i_0 j_0}$ can be determined by the lower bound and the maximum potential range of the fuzzy number of all alternatives with respect to the j_0-th criterion.

$$\begin{gathered} a^l_{i_0 j_0} = \max(b^u_{ij_0}) \\ \text{where} \\ i \in Q \\ b^u_{ij_0} = \begin{cases} a_{ij_0}, & \hat{a}_{ij_0} \in N_1 \\ a^u_{ij_0}, & \hat{a}_{ij_0} \in N_2 \\ a^U_{ij_0}, & \hat{a}_{ij_0} \in N_3 \end{cases} \end{gathered} \tag{14}$$

$$\begin{gathered} a^u_{i_0 j_0} = a^l_{i_0 j_0} + \max(\vartheta_{ij_0}) \\ \text{where} \\ i = 1, \ldots, m \\ \vartheta_{ij_0} = \begin{cases} 0, & \hat{a}_{ij_0} \in N_1 \\ a^u_{ij_0} - a^l_{ij_0}, & \hat{a}_{ij_0} \in N_2 \\ a^U_{ij_0} - a^L_{ij_0}, & \hat{a}_{ij_0} \in N_3 \end{cases} \end{gathered} \tag{15}$$

- If this alternative is worse than a set of alternatives $\boldsymbol{R}$, the value of the alternative $\hat{a}_{i_0 j_0} = [a^l_{i_0 j_0}, a^u_{i_0 j_0}]$ can be determined by **Eqs.(16)-(17)**. The upper bound of $\hat{a}_{i_0 j_0}$ can be determined by the minimum value of alternatives in the set $\boldsymbol{R}$ with respect to the j_0 -th criterion. The lower bound of $\hat{a}_{i_0 j_0}$ can be determined by the upper bound and the maximum potential range of the fuzzy number of all alternatives with respect to the j_0 -th criterion. But the lower bound should be a positive number.

$$a_{i_0 j_0}^{l} = \max[(a_{i_0 j_0}^{u} - \max(\vartheta_{ij_0})),0]$$
where
$$i = 1, \ldots, m$$
$$\vartheta_{ij_0} = \begin{cases} 0, & \hat{a}_{ij_0} \in N_1 \\ a_{ij_0}^{u} - a_{ij_0}^{l}, & \hat{a}_{ij_0} \in N_2 \\ a_{ij_0}^{U} - a_{ij_0}^{L}, & \hat{a}_{ij_0} \in N_3 \end{cases} \tag{16}$$

$$a_{i_0 j_0}^{u} = \min(b_{ij_0}^{l})$$
where
$$i \in Q$$
$$b_{ij_0}^{l} = \begin{cases} a_{ij_0}, & \hat{a}_{ij_0} \in N_1 \\ a_{ij_0}^{l}, & \hat{a}_{ij_0} \in N_2 \\ a_{ij_0}^{L}, & \hat{a}_{ij_0} \in N_3 \end{cases} \tag{17}$$

- If this alternative is described as the highest or the best for benefit-type criterion or the worst for cost-type criterion, the value of the alternative $\hat{a}_{i_0 j_0} = [a_{i_0 j_0}^{l}, a_{i_0 j_0}^{u}]$ can be determined by **Eqs.(18)-(19)**. The lower bound of $\hat{a}_{i_0 j_0}$ can be determined by the maximum value of all other alternatives with respect to the j_0-th criterion. The upper bound of $\hat{a}_{i_0 j_0}$ can be determined by the lower bound and the maximum potential range of the fuzzy number of all alternatives with respect to the j_0-th criterion.

$$a_{i_0 j_0}^{l} = \max(b_{ij_0}^{u})$$
where
$$i = 1,2, \ldots, i_0 - 1, i_0 + 1, \ldots, m$$
$$b_{ij_0}^{u} = \begin{cases} a_{ij_0}, & \hat{a}_{ij_0} \in N_1 \\ a_{ij_0}^{u}, & \hat{a}_{ij_0} \in N_2 \\ a_{ij_0}^{U}, & \hat{a}_{ij_0} \in N_3 \end{cases} \tag{18}$$

$$a_{i_0 j_0}^{u} = a_{i_0 j_0}^{l} + \max(\vartheta_{ij_0})$$
where
$$i = 1, \ldots, m$$
$$\vartheta_{ij_0} = \begin{cases} 0, & \hat{a}_{ij_0} \in N_1 \\ a_{ij_0}^{u} - a_{ij_0}^{l}, & \hat{a}_{ij_0} \in N_2 \\ a_{ij_0}^{U} - a_{ij_0}^{L}, & \hat{a}_{ij_0} \in N_3 \end{cases} \tag{19}$$

- If this alternative is described as the lowest or the worst for benefit-type criterion or the best for cost-type criterion, the value of the alternative $\hat{a}_{i_0 j_0} = [a^l_{i_0 j_0}, a^u_{i_0 j_0}]$ can be determined by **Eqs.(20)-(21)**. The upper bound of $\hat{a}_{i_0 j_0}$ can be determined by the minimum value of all other alternatives with respect to the j_0-th criterion. The lower bound of $\hat{a}_{i_0 j_0}$ can be determined by the upper bound and the maximum potential range of the fuzzy number of all alternatives with respect to the j_0-th criterion.

$$\begin{gathered} a^l_{i_0 j_0} = \max[(a^u_{i_0 j_0} - \max(\vartheta_{i j_0})),0] \\ i = 1,\dots,m \\ \vartheta_{i j_0} = \begin{cases} 0, & \hat{a}_{i j_0} \in N_1 \\ a^u_{i j_0} - a^l_{i j_0}, & \hat{a}_{i j_0} \in N_2 \\ a^U_{i j_0} - a^L_{i j_0}, & \hat{a}_{i j_0} \in N_3 \end{cases} \end{gathered} \tag{20}$$

$$\begin{gathered} a^u_{i_0 j_0} = \min(b^l_{i j_0}) \\ i = 1,2,\dots,i_0 - 1, i_0 + 1,\dots,m \\ b^l_{i j_0} = \begin{cases} a_{i j_0}, & \hat{a}_{i j_0} \in N_1 \\ a^l_{i j_0}, & \hat{a}_{i j_0} \in N_2 \\ a^L_{i j_0}, & \hat{a}_{i j_0} \in N_3 \end{cases} \end{gathered} \tag{21}$$

- If this alternative is better than a set of alternatives ***Q***, but is worse than a set of alternatives ***R***, then the value of the alternative $\hat{a}_{i_0 j_0} = [a^l_{i_0 j_0}, a^u_{i_0 j_0}]$ can be determined by **Eqs.(22)-(23)**. The lower bound of $\hat{a}_{i_0 j_0}$ can be determined by the maximum value of alternatives in the set ***Q*** with respect to the j_0-th criterion. The upper bound of $\hat{a}_{i_0 j_0}$ can be determined by the minimum value of alternatives in the set ***R*** with respect to the j_0-th criterion.

$$a_{i_0 j_0}^{l} = \max(b_{ij_0}^{u}) \quad \text{where} \quad i \in Q \quad b_{ij_0}^{u} = \begin{cases} a_{ij_0}, & \hat{a}_{ij_0} \in N_1 \\ a_{ij_0}^{u}, & \hat{a}_{ij_0} \in N_2 \\ a_{ij_0}^{U}, & \hat{a}_{ij_0} \in N_3 \end{cases} \tag{22}$$

$$a_{i_0 j_0}^{u} = \min(b_{ij_0}^{l}) \quad \text{where} \quad i \in R \quad b_{ij_0}^{l} = \begin{cases} a_{ij_0}, & \hat{a}_{ij_0} \in N_1 \\ a_{ij_0}^{l}, & \hat{a}_{ij_0} \in N_2 \\ a_{ij_0}^{L}, & \hat{a}_{ij_0} \in N_3 \end{cases} \tag{23}$$

- If this alternative is described as about average, the value of the alternative $\hat{a}_{i_0 j_0} = [a_{i_0 j_0}^{L}, a_{i_0 j_0}^{M}, a_{i_0 j_0}^{U}]$ can be determined by **Eqs.(24)-(26)**. The value of this alternative can be determined by the average value of all other alternatives for the upper, most possible, and the lower bound, respectively.

$$a_{i_0 j_0}^{L} = \frac{\sum_{i \neq i_0} b_{ij_0}^{L}}{m-1} \quad \text{where} \quad i = 1,2,\ldots,m \quad b_{ij_0}^{L} = \begin{cases} a_{ij_0}, & \hat{a}_{ij_0} \in N_1 \\ a_{ij_0}^{l}, & \hat{a}_{ij_0} \in N_2 \\ a_{ij_0}^{L}, & \hat{a}_{ij_0} \in N_3 \end{cases} \tag{24}$$

$$a_{i_0 j_0}^{M} = \frac{\sum_{i \neq i_0} b_{ij_0}^{M}}{m-1} \quad \text{where} \quad i = 1,2,\ldots,m \quad b_{ij_0}^{M} = \begin{cases} a_{ij_0}, & \hat{a}_{ij_0} \in N_1 \\ \frac{a_{ij_0}^{l} + a_{ij_0}^{u}}{2}, & \hat{a}_{ij_0} \in N_2 \\ a_{ij_0}^{M}, & \hat{a}_{ij_0} \in N_3 \end{cases} \tag{25}$$

$$a^U_{i_0j_0}=\frac{\sum_{i\neq i_0} b^U_{ij_0}}{m-1}$$
where
$$i=1,2,\ldots,m \tag{26}$$
$$b^U_{ij_0}=\begin{cases} a_{ij_0}, & \hat{a}_{ij_0}\in N_1\\ a^u_{ij_0}, & \hat{a}_{ij_0}\in N_2\\ a^U_{ij_0}, & \hat{a}_{ij_0}\in N_3\end{cases}$$

Based on the equations above, the numerical data for each alternative can be obtained. It is worth attention that if the values with respect to the reference criteria are empty too, the reference criteria should be determined before the value of other criteria can be determined.

Step 3. Normalization. Normalization can be conducted by **Eqs.(27)-(28)** where ref. [38] is applied as the method of distance measure.

$$\hat{x}_{ij}=\begin{cases} x_{ij}=\frac{a_{ij}-D^l_j}{D^u_j-D^l_j}, & \hat{a}_{ij}\in N_1\\ (x^l_{ij},x^u_{ij})=(\frac{a^l_{ij}-D^l_j}{D^u_j-D^l_j},\frac{a^u_{ij}-D^l_j}{D^u_j-D^l_j}), & \hat{a}_{ij}\in N_2 \quad j\in B\\ (x^L_{ij},x^M_{ij},x^U_{ij})=(\frac{a^L_{ij}-D^l_j}{D^u_j-D^l_j},\frac{a^M_{ij}-D^l_j}{D^u_j-D^l_j},\frac{a^U_{ij}-D^l_j}{D^u_j-D^l_j}), & \hat{a}_{ij}\in N_3\end{cases} \tag{27}$$

$$\hat{x}_{ij}=\begin{cases} x_{ij}=\frac{D^u_j-a_{ij}}{D^u_j-D^l_j}, & \hat{a}_{ij}\in N_1\\ (x^l_{ij},x^u_{ij})=(\frac{D^u_j-a^u_{ij}}{D^u_j-D^l_j},\frac{D^u_j-a^l_{ij}}{D^u_j-D^l_j}), & \hat{a}_{ij}\in N_2 \quad j\in C\\ (x^L_{ij},x^M_{ij},x^U_{ij})=(\frac{D^u_j-a^U_{ij}}{D^u_j-D^l_j},\frac{D^u_j-a^M_{ij}}{D^u_j-D^l_j},\frac{D^u_j-a^L_{ij}}{D^u_j-D^l_j}), & \hat{a}_{ij}\in N_3\end{cases} \tag{28}$$

where *B* indicates the benefit-type criteria, *C* represents the cost-type criteria. D^l_j and D^u_j are the minimum and maximum values of the *j*-th criterion and determined by **Eqs.(29)-(30)**; N_1, N_2, N_3 indicate the data of the crisp numbers, interval numbers, and triangular fuzzy numbers, respectively.

$$D_j^l = \min_i (d_{ij}^l)$$
$$d_j^l = \begin{cases} a_{ij}, & \hat{a}_{ij} \in N_1 \\ a_{ij}^l, & \hat{a}_{ij} \in N_2 \\ a_{ij}^L, & \hat{a}_{ij} \in N_3 \end{cases} \quad (29)$$

$$D_j^u = \max_i (d_{ij}^u)$$
$$d_j^u = \begin{cases} a_{ij}, & \hat{a}_{ij} \in N_1 \\ a_{ij}^u, & \hat{a}_{ij} \in N_2 \\ a_{ij}^U, & \hat{a}_{ij} \in N_3 \end{cases} \quad (30)$$

After normalization of the data, all the criteria have been shifted to benefit-type criteria, and all the data in the decision-making matrix can be transformed into values between 0 and 1. Accordingly, the normalized decision-making matrix *X* can also be obtained, as presented in **Eq.(31)**.

$$X = \begin{bmatrix} \hat{x}_{11} & \hat{x}_{12} & \cdots & \hat{x}_{1n} \\ \hat{x}_{21} & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ \hat{x}_{m1} & \cdots & \cdots & \hat{x}_{mn} \end{bmatrix} \quad (31)$$

Step 4. Choosing the ideal criterion value. An ideal alternative with all ideal values for all the criteria is constructed as a reference for sustainability performance judgment. The value of the ideal alternative regarding the *j*-th criterion can be determined by **Eq.(32).**

$$\hat{x}_j^+ = (x_j^{+L}, x_j^{+M}, x_j^{+U}) \quad (32)$$

where x_j^{+L}, x_j^{+M} and x_j^{+U} represent the lower bound, most possible value, and the upper bound of the triangular fuzzy number respectively and are determined by **Eqs.(33) -(35)**.

$$x_j^{+L} = \max_i (c_{ij}^L)$$
$$c_{ij}^L = \begin{cases} x_{ij}, & \hat{x}_{ij} \in N_1 \\ x_{ij}^l, & \hat{x}_{ij} \in N_2 \\ x_{ij}^L, & \hat{x}_{ij} \in N_3 \end{cases} \tag{33}$$

$$x_j^{+M} = \max_i (c_{ij}^M)$$
$$c_{ij}^M = \begin{cases} x_{ij}, & \hat{x}_{ij} \in N_1 \\ \frac{x_{ij}^l + x_{ij}^u}{2}, & \hat{x}_{ij} \in N_2 \\ x_{ij}^M, & \hat{x}_{ij} \in N_3 \end{cases} \tag{34}$$

$$x_j^{+U} = \max_i (c_{ij}^U)$$
$$c_{ij}^U = \begin{cases} x_{ij}, & \hat{x}_{ij} \in N_1 \\ x_{ij}^u, & \hat{x}_{ij} \in N_2 \\ x_{ij}^U, & \hat{x}_{ij} \in N_3 \end{cases} \tag{35}$$

Step 5. Calculating grey relational coefficient. The grey relational coefficient can be calculated by using **Eq.(36)**.

$$\gamma_{ij} = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{ij} + \zeta \Delta_{\max}} \quad i = 1,2,\ldots,m, j = 1,2,\ldots,n \tag{36}$$

where Δ_{ij} represents the distance of the *j*-th criterion with regard to the *i*-th alternative to that of the ideal option and is determined by **Eq.(37)**; $\zeta \in [0,1]$is the distinguishing coefficient; $\Delta_{\min}$and $\Delta_{\max}$ represent the minimum and maximum values of criteria differences, respectively, which are shown in **Eqs. (38)-(39)**.

$$\Delta_{ij} = \hat{x}_j^+ - \hat{x}_{ij} = \begin{cases} x_{ij}^{+M} - x_{ij}, & \hat{x}_{ij} \in N_1 \\ \max(x_{ij}^{+L} - x_{ij}^l, x_{ij}^{+U} - x_{ij}^u), & \hat{x}_{ij} \in N_2 \\ \max(x_{ij}^{+L} - x_{ij}^L, x_{ij}^{+M} - x_{ij}^M, x_{ij}^{+U} - x_{ij}^U), & \hat{x}_{ij} \in N_3 \end{cases} \tag{37}$$

$$\Delta_{\min} = \min_i \min_j \Delta_{ij} \quad i = 1,2,\ldots,m, j = 1,2,\ldots,n \tag{38}$$

$$\Delta_{\max} = \max_i \max_j \Delta_{ij} \quad i = 1,2,\ldots,m, j = 1,2,\ldots,n \tag{39}$$

Step 6. Calculating grey relational grade. The grey relational grade of the i-th alternative can be calculated by determining the weighted sum of all the grey relational coefficients, as presented in **Eq.(40)**.

$$\Gamma_i = \sum_{j=1}^{n} w_j \gamma_{ij} \quad i = 1,2,\ldots,m \tag{40}$$

The alternatives thereafter can be prioritized by ranking grey relational grades in descending orders.

3. Case study

A hypothetical case based on the Ref. [39] about electricity generation scenarios selection was studied by using the proposed methods. There were five alternatives listed in the case study which were Systems 1-5. To evaluate the performance of the five electricity generation systems, four criteria were selected from each aspect including environmental, economic, and social aspects, and 12 criteria were selected in total (see **Table 9**). In the economic aspect, economic dispatch, capital cost, operation, and maintenance cost, and fuel cost are considered as the indicators for measuring economic performances. From an environmental perspective, the indicators including recyclability, global warming, freshwater ecotoxicity, and land occupation are used. For the social aspect, total employment, worker injuries, human toxicity potential, and depletion of fossil fuels are adapted as indicators for social sustainability assessment. Among those criteria, the benefit-type criteria in this case include economic dispatch, recyclability, and total employment. The remaining criteria including capital cost, operation and maintenance cost, fuel cost, global warming, freshwater ecotoxicity, land occupation, worker injuries, human toxicity potential, and depletion of fossil fuels belong to cost-type criteria.

Table 9. Criteria system

Criteria		**Unit**
Economic		
Economic dispatch	(EC1)	no units
Levelised cost: capital	(EC2)	£/MWh
Levelised cost: Operation and Maintenance	(EC3)	£/MWh
Levelised cost: fuel	(EC4)	£/MWh
Environmental		
Recyclability	(EN1)	ratio
Global warming	(EN2)	kg CO_2 eq/kWh
Freshwater ecotoxicity	(EN3)	kg DCB eq/kWh
Land occupation	(EN4)	m^2yr
Social		
Employment: total	(S1)	person-years/TWh
Worker injuries	(S2)	injuries/TWh
Human toxicity potential	(S3)	kg DCB eq/kWh
Depletion of fossil fuels	(S4)	MJ/kWh

The data of the three hypothetical cases constructed by the authors for illustrating Type I, and Type II, and Type II hybrid types are shown in **Supplementary Materials Table A1-A3**. As for the Type I dataset, the data of the same criterion should share the same data types. Therefore, the data with respect to the economic dispatch is revised as linguistic terms, and that with respect to the recyclability is revised as interval numbers. The crisp numbers are used for the employment and worker injuries. The triangular fuzzy numbers are used for the remaining criteria. As for the Type II dataset, the data of the same alternative use the same data type. Therefore, crisp numbers, triangular fuzzy numbers, comparative linguistic terms, interval numbers, and grading linguistic terms are used to describe these five electricity generation systems, respectively. Type III hybrid type contains different data types in both column and row. In this study, the dataset of Type III is a mix of Type I and Type II datasets.

3.1 Determining the weights

The first step is to determine the criteria weights by using BWM according to **Eqs.(2)-(5)**. Taking the calculations of the weights of different aspects as an example.

Step 1. The set of decision criteria $C = (c_1, c_2, c_3)$ is determined and c_1, c_2, c_3 refer to economic, environmental, and social aspects, respectively.

Step 2. The environmental aspect and the economic aspect are selected as the most important criterion and the less important criterion and written as c_B and c_W, respectively, because the environmental aspect plays a significant role in sustainability and has a larger influence on the whole world. By contrast, the economic aspect is merely related to the benefit of a company.

Step 3. Since environmental aspect has been recognized as “significantly important” than economic aspects in this study, the value of a_{B1} is assigned as 4. The environmental aspect is relatively important to the social aspect, because the environmental aspect has a long-term impact on the livelihood of the earth. So, the value of a_{B3} is 2. The last one, a_{B2}, can also be presented as$a_{BB}=1$. Therefore, the resulting Best-to-Others vector is shown in **Eq.(41)**.

$$A_B = (a_{B1}, a_{B2}, a_{B3})=(4,1,2) \quad (41)$$

Step 4. Similarly, the resulting Others-to-Worst vector can be determined by **Eq.(3)** as shown in **Eq.(42)**.

$$A_W = (a_{1W}, a_{2W}, a_{3W})^T=(1,4,2)^T \quad (42)$$

Step 5. The optimal weights can be determined by solving **Eq.(4)** as shown in **Eq.(43)**.

$$
\begin{aligned}
&\min \xi \\
&s.t. \\
&\left|\frac{w_1}{w_1} - 1\right| \le \xi \\
&\left|\frac{w_1}{w_2} - 4\right| \le \xi \\
&\left|\frac{w_1}{w_3} - 2\right| \le \xi \\
&\left|\frac{w_1}{w_2} - 4\right| \le \xi \\
&\left|\frac{w_2}{w_2} - 1\right| \le \xi \\
&\left|\frac{w_3}{w_2} - 2\right| \le \xi \\
&w_1 + w_2 + w_3 = 1 \\
&w_1, w_2, w_3 \ge 0
\end{aligned} \tag{43}
$$

The solution $(w_1^*, w_2^*, w_3^*) = (0.143, 0.571, 0.286)$ is determined by solving the **Eq.(43)**. The consistency ratio is obtained by using **Eq.(5)** as shown in **Eq.(44)**. According to **Table 6**, the consistency index should be 1.63 since the maximum ratio used in this study is 4.

$$CR = \frac{\xi^*}{CI} = \frac{0}{1.63} = 0 \tag{44}$$

Since CR<0.1, the aspect weights are feasible and acceptable. Similar to determining the weights of these three aspects, the criteria in each aspect are adopted as inputs for BWM and the corresponding local weights of the criteria in each aspect can be obtained, respectively. The results are shown in **Table 10**.

Then the global weights can be determined by **Eq.(45)** and the results are shown in **Table 10**.

$$w_j = w_p \times w_k \tag{45}$$

where w_j represent the global weight of the *j*-th criterion. w_p indicates the aspect weight of the *p*-th aspect which the *j*-th criterion belongs to. w_k represents the local weight of the *k*-th criterion in the *p*-th aspect.

Table 10. Criteria weights

Aspect	Aspect weight	Criterion	Local weight	Global weight
Economic	0.143	Economic dispatch	0.500	0.071
		Levelised cost: capital	0.167	0.024
		Levelised cost: O and M	0.167	0.024
		Levelised cost: fuel	0.167	0.024
Environmental	0.571	Recyclability	0.429	0.245
		Global warming	0.286	0.163
		Freshwater ecotoxicity	0.143	0.082
		Land occupation	0.143	0.082
Social	0.286	Employment: total	0.167	0.048
		Worker injuries	0.333	0.095
		Human toxicity potential	0.333	0.095
		Depletion of fossil fuels	0.167	0.048

3.2 Alternatives ranking

Then the electricity generation pathways in those three cases were prioritized by using the iGRA-MH method according to **Eqs.(14)-(40),** respectively. To better illustrate the calculation process of the model, the dataset of Type II hybrid information (see **Supplementary Materials Table A2**) was taken as an example.

Step 1. The missing information has been filled by linguistic terms as presented in **Supplementary Materials Table A2.**

Step 2. The data for System 3 and System 5 are recognized as level-grading linguistic terms and comparative linguistic terms respectively. They need to be transformed expressions to numerical terms. As for level-grading linguistic terms, the information will be transformed into triangular fuzzy numbers according to **Table 8** and will be added to the matrix after normalization. Taking economic dispatch with regards to System 5 as an example, the expression "very good" can be transformed to (0.8,0.9,1.0). As for comparative linguistic terms, the data can be transformed into interval numbers in step 2 according to **Eqs.(14)-(26)**. Taking depletion of fossil fuels with regards to System 3 as an example, it is recognized as "the best" one for a cost-type criterion. Therefore, the value could be transformed according to **Eqs.(20)-(21)** as shown in **Eq.(46)**.

$$\hat{a}_{312} = [a_{312}^{l}, a_{312}^{u}] \tag{46}$$

where

$$a_{312}^{u} = \min(a_{112}, a_{212}^{L}, a_{412}^{l}) = 0.0574$$

$$a_{312}^{l} = \max\left[\left(a_{312}^{u} - \max(\vartheta_{112}, \vartheta_{212}, \vartheta_{412})\right), 0\right]=0$$

Similarly, the remaining data of the Systems 3 and 5 can be transformed into numerical terms.

Step 3. According to **Eqs.(27)-(28)**, the normalized decision-making matrix can be determined. The recyclable ratio with regard to System 2 can be used as an example of benefit-type criteria, and the normalization is proceeded by **Eq.(47)**. The fuel cost regarding System 1 is used as an instance for cost-type criteria, then the normalized value could be determined by **Eq.(48)**.

$$\hat{x}_{24} = (x_{24}^L, x_{24}^M, x_{24}^U) = (\frac{a_{24}^L - D_4^l}{D_4^u - D_4^l}, \frac{a_{24}^M - D_4^l}{D_4^u - D_4^l}, \frac{a_{24}^U - D_4^l}{D_4^u - D_4^l}) = (0,0.495,0.495) \quad (47)$$

$$\hat{x}_{13} = x_{13} = \frac{D_3^u - a_{13}}{D_3^u - D_3^l} = 0.697 \quad (48)$$

Similarly, all data originally from **Table A2** can be normalized accordingly.

Step 4. The ideal criterion value can be determined by **Eq.(32)**, and the results are presented in **Eq.(49)**.

$$X^{+} = \begin{pmatrix} (0.800,0.900,1.000) \\ (0.990,0.999,1.000) \\ (1.000,1.000,1.000) \\ (1.000,1.000,1.000) \\ (0.700,0.800,1.000) \\ (0.991,0.996,1.000) \\ (0.695,0.957,1.000) \\ (0.989,0.994,1.000) \\ (1.000,1.000,1.000) \\ (1.000,1.000,1.000) \\ (0.912,0.985,1.000) \\ (0.996,0.998,1.000) \end{pmatrix} \quad (49)$$

Step 5. The grey relational coefficient can be calculated using **Eq.(36)-(39)**. For example, the grey relational coefficient for recyclability with regard to System 1 can be calculated as **Eq.(50)**. The distinguishing coefficient ζ=0.5 is assigned. The distinguishing coefficient refers to how much the largest difference has an impact on the final result. If the distinguishing coefficient is closer to 1, more impact is considered in the final score. If it is closer to 0, less impact of the largest difference is considered. In this case study, the middle number is chosen, to balance the impacts.

$$\gamma_{14} = \frac{\Delta_{\min}+\zeta\Delta_{\max}}{\Delta_{14}+\zeta\Delta_{\max}} = \frac{0+0.5\times 1}{0.555+0.5\times 1} = 0.474 \tag{50}$$

Similarly, the grey relational coefficient for all the data values in the decision-making matrix could be obtained.

Step 6. The grey relational grade can be determined by **Eq.(40)**, and the grey relational grade of the example of System 1 is presented as **Eq.(51)**.

$$\Gamma_1 = \sum_{j=1}^{12} w_j \gamma_{1j} = 0.071 \times 0.547 + 0.023 \times 0.682 + \ldots + 0.048 \times 0.334 = 0.4327 \tag{51}$$

Then, the grey relational grade of Systems 2-5 can be calculated similarly to that of System 1. The alternatives will be finally prioritized by descending grey relational grades. Similar to the Type II hybrid dataset, the final results of iGRA-MH by adopting Type I and Type III hybrid data are shown in **Table 11**.

Table 11. Results of iGRA-MH

	Type I		Type II		Type III	
	Score	Rank	Score	Rank	Score	Rank
System 1	0.474	5th	0.433	5th	0.493	5th

System 2	0.725	3rd	0.647	3rd	0.747	3rd
System 3	0.815	2nd	0.681	2nd	0.770	2nd
System 4	0.853	1st	0.770	1st	0.893	1st
System 5	0.676	4th	0.600	4th	0.564	4th

4. Result and discussion

4.1 Case study result

As shown in **Table 11**, the case studies with different hybrid data types generate the same ranking results through the proposed MCDM framework. The prioritization sequence of this case study is System 4 > System 3 > System 2 > System 5 > System 1. The result is consistent with the data in ref. [39]. Based on the ref. [39], System 4 is superior among all electricity generation alternatives in fuel cost, recyclability ratio, global warming, land occupation, employment, human toxicity potential, and depletion of fossil fuels. System 3 is the second priority among all alternatives. According to the study of Stamford and Azapagic [39], System 3 performs well in global warming and worker injuries and has average performance on the other criteria. System 2 is more sustainable than System 5 and System 1. Known from the original dataset, System 2 performs better in capital cost, operation and maintenance cost, global warming, freshwater ecotoxicity, land occupation, worker injuries, and human toxicity potential. System 5 is more sustainable than System 1 according to ranking results in most of the criteria, including economic dispatch, fuel cost, recyclability ratio, global warming, freshwater ecotoxicity, land occupation, employment, human toxicity potential, and depletion of fossil fuels. It is obvious that System 5 performs better in the environmental aspect comparing to System 1.

As explained above, the sustainable prioritization framework has been proved feasible and rational, since the ranking result is consistent with a real-life situation. Apart from that, the results of the framework show its consistency and accuracy. Known from **Table 11**, the ranking results of three different hybrid data types are the same. It shows the consistency and accuracy of the iGRA-MH framework. The results of the prioritization framework under hybrid information are robust with the change of data types.

4.2 Evaluation

To further evaluate the feasibility and consistency of generation results, the fuzzy GRA [40] was also used to rank these five alternatives. The data of the same alternatives as selected in the case study presented in ref. [39] was used for this evaluation. In this study, the minimum and maximum values are recognized as the lower and upper bound in the fuzzy number, and the central numbers are assumed to be the middle number in the fuzzy number. The details of the evaluation are presented in **Supplementary Materials Part IV**. Based on the assumption above, the results are shown in **Table 12**.

Table 12. Results generated by fuzzy GRA

	Score	Rank
System 1	0.474	5th

System 2	0.725	3rd
System 3	0.815	2nd
System 4	0.853	1st
System 5	0.676	4th

The ranking results generated by both methods are consistent which indicated the feasibility of the iGRA-MH model. As the feasibility of fuzzy GRA has been proven in ref. [40], the feasibility and accuracy of iGRA-MH have been revealed as well.

To validate the feasibility of the proposed method, the Pearson's correlation coefficients between the case study result and the comparison results are calculated based on the equations below[41].

$$Cor(A,B) = \frac{\sum_i^m (A_i-\bar{A})(B_i-\bar{B})}{\sqrt{\sum_i^m (A_i-\bar{A})^2}\sqrt{\sum_i^m (B_i-\bar{B})^2}} \quad (52)$$

where A refers to the result of alternatives determined by the proposed method. B refers to the result of alternatives determined by evaluation method, A_i refers to the value of the i-th alternative based on the proposed method. B_i refers to the value of the i-th alternative based on the evaluation method. $\bar{A}$ and $\bar{B}$ indicate the average value of score for the proposed method and evaluation method, respectively.

The coefficients are presented in **Table 13**.

Table 13. Pearson's correlation coefficients between different hybrid types and the evaluation result

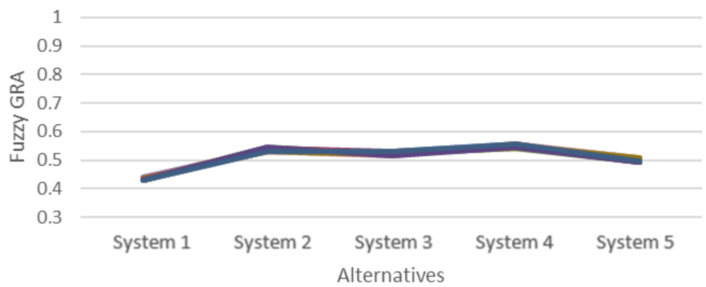
	Type I	**Type II**	**Type III**

Pearson's correlation coefficients	0.955	0.950	0.976

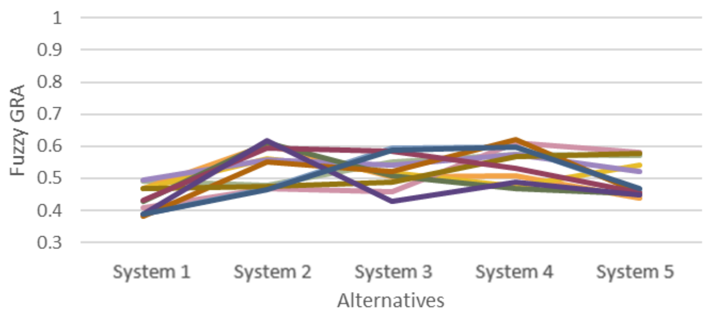
The higher the value of the correlation coefficient is, the more correlated the two results are. Because the fuzzy GRA model has been peer-reviewed, the evaluation result is regarded as the recommended prioritization. In this case, the higher the value of the coefficient, the more accurate the result is. Based on this case study, Hybrid Type II is recognized as slightly more difficult to be treated and transformed to accurate numbers, because the Pearson's correlation coefficient for Hybrid Type II and the evaluation result is slightly lower than that of other hybrid types. Since all coefficients are close to 1, the ranking results of three hybrid types are highly correlated to the result of fuzzy GRA. Therefore, the proposed method for three hybrid types can be recognized as effective and feasible.

4.3 Sensitivity analysis

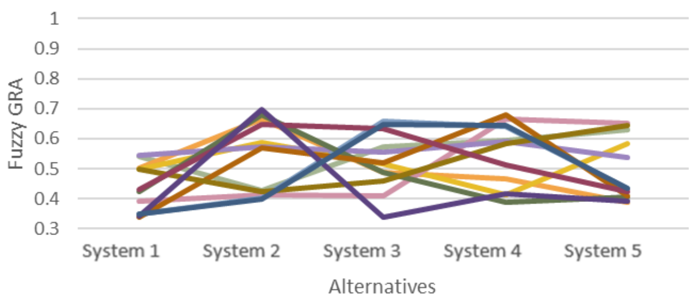
In this study, sensitivity analysis is used to evaluate the robustness and objectiveness of the model by testing the model while changing the criteria weights. The sustainability prioritization framework will be conducted repeatedly with different criteria weights. In every running, one of the criteria will be set as the major criterion and the other as minor criteria. To investigate the influence of changing the weight of a specific criterion (major criterion), the weight of one criterion will be set as the largest values in turn while the weights of other criteria are the same. This one criterion is called major criterion. In addition, the total values of weights should always be equal to 1. Therefore, we conducted three sensitivity analyses for three different sets of criteria weights. In the first test, the weight of the major criterion is 0.12 and the weights of the minor criteria are 0.08. Secondly, 0.45 and 0.05 are used as the weights for the major criterion and minor criteria, respectively. Lastly, the weights of major and minor criteria are 0.78 and 0.02, respectively. The differences of weights between major and minor criteria are increasing to test the robustness of the model. The results of sensitivity analysis are shown in **Figs.4-7**.



a) w=0.12 for the major criterion and w=0.08 for the others

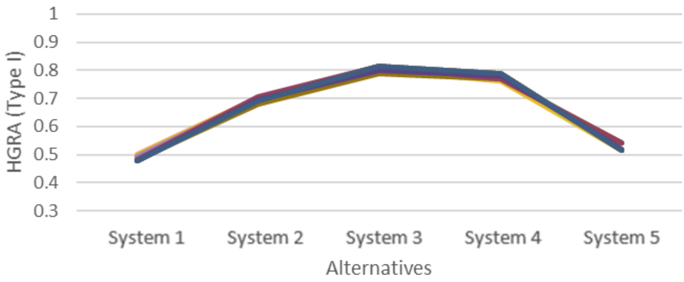


b) w=0.45 for the major criterion and w=0.05 for the others

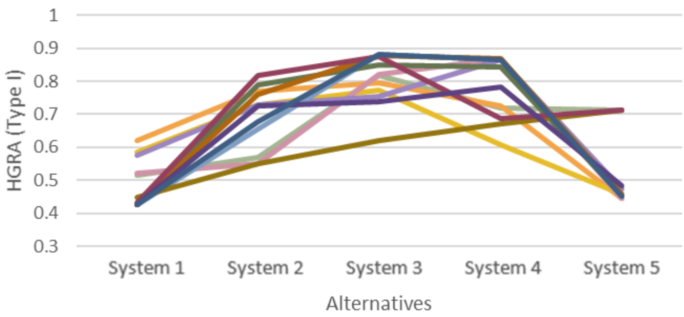


c) w=0.78 for the major criterion and w=0.02 for the others

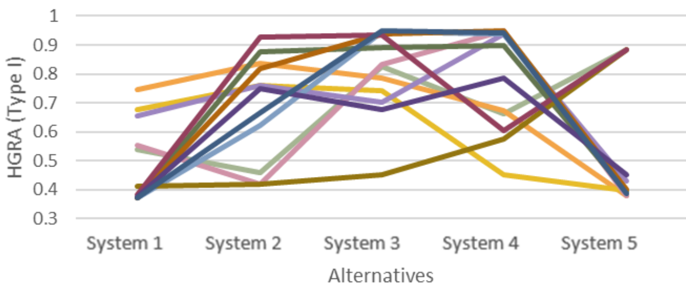
Figure 4. Sensitivity analysis results of Fuzzy GRA



a) w=0.12 for the major criterion and w=0.08 for the others

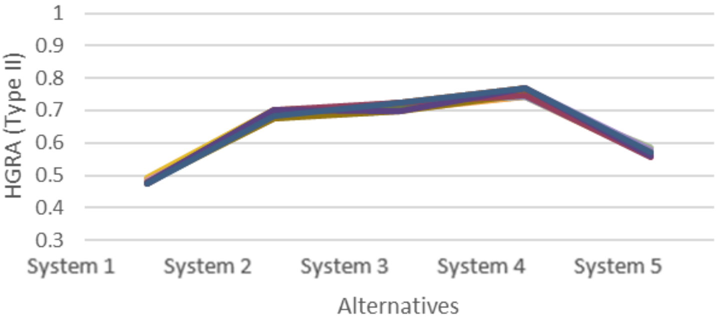


b) w=0.45 for the major criterion and w=0.05 for the others

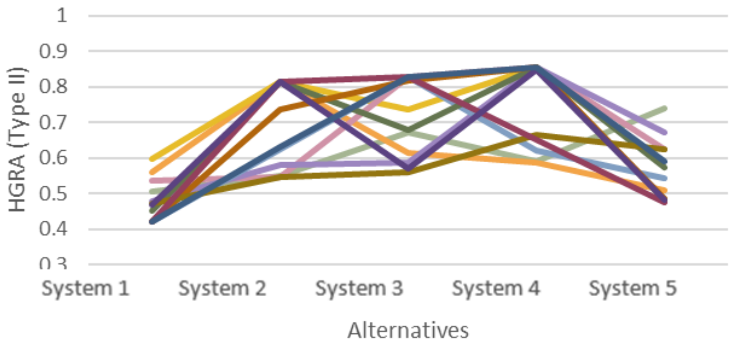


c) w=0.78 for the major criterion and w=0.02 for the others

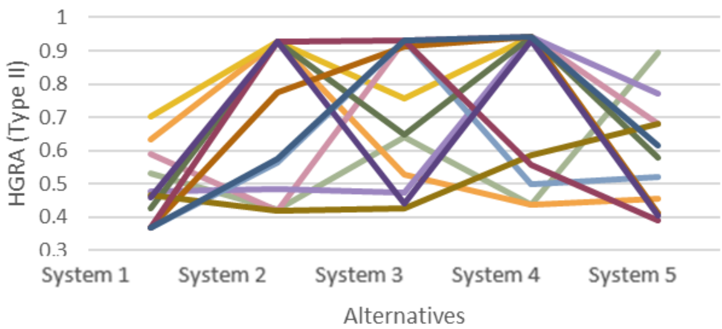
Figure 5. Sensitivity analysis results of iGRA-MH (Type I)



a) w=0.12 for the major criterion and w=0.08 for the others



b) w=0.45 for the major criterion and w=0.05 for the others



c) w=0.78 for the major criterion and w=0.02 for the others

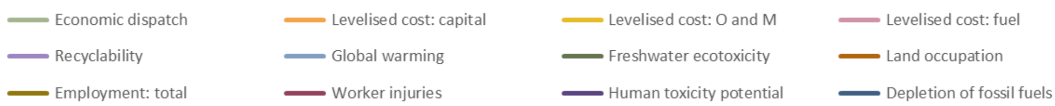
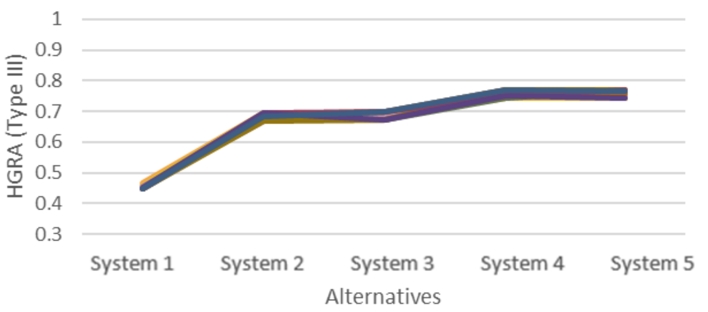
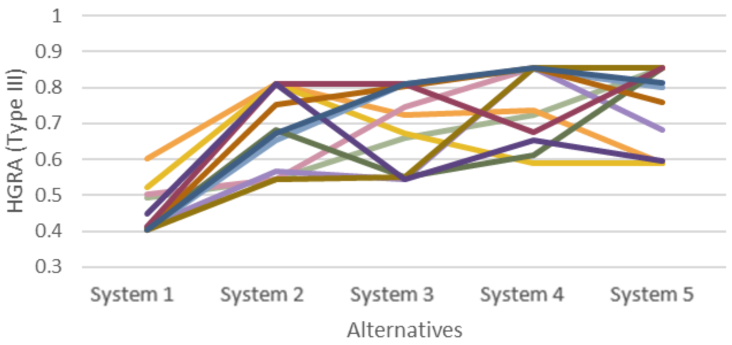


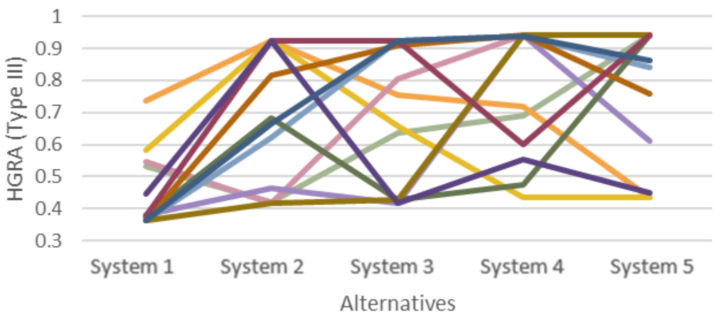
Figure 6. Sensitivity analysis results of iGRA-MH (Type II)



a) w=0.12 for the major criterion and w=0.08 for the others



b) w=0.45 for the major criterion and w=0.05 for the others



c) w=0.78 for the major criterion and w=0.02 for the others

Figure 7. Sensitivity analysis results of iGRA-MH (Type III)

Fig.4 illustrates the sensitivity analysis results of the fuzzy GRA model. **Figs.5-7** illustrate the sensitivity analysis results of the iGRA-MH model based on three datasets (shown in **Supplementary Materials Table A1-A3)**. According to **Fig.7**, the ranking results changed with a swift of the major criterion. The model is more robust if the ranking sequence changes less when the major criterion swifts. based on this concept, if the lines show the same trend, the model is less sensitive. It is obvious that when the difference between the weights of major criterion and minor criterion increases the model will present higher sensitivity. Since All the diagrams show similar complexity and clutter, the hybrid MCDM model proposed in this study achieved the same robustness level as the fuzzy GRA.

Based on the illustration of **Fig.7**, when the weight of the major criterion is slightly higher than the weight of the minor criterion, the ranking of alternative keeps the same. On the one hand, the ranking results show that the prioritized sequences in each model have slight differences, but they are basically similar. System 1 definitively is the worst option in this decision-making case, and System 4 is one of the top options. On the other hand, the ranking results are similar but slightly different in these four figures, which means the revised hybrid information is slightly different from what is shown in ref. [39]. This phenomenon might be led by the uncertainty of linguistic expression, especially the comparative linguistic expression. For instance, System 5 performs the best in the fuel cost among all alternatives, since the source of System 5 is free of charge. When the decision-makers describe the performance of the alternative with respect to this criterion by using “the best”, the value will be quantified by analysing the maximum value of this criterion regarding all alternatives except System 5. In this case study, the fuel cost of System 4 is 0 £ /kWh as well, so the quantified value of this criterion of System 5 is 0 £ /kWh. But if System 4 is excluded from this decision-making, then the value will be determined as [0,4.2] based on the proposed transformation method. The error will be accumulated and led to differences in prioritization results. Therefore, the proposed MCDM method under hybrid information is feasible but the results will be affected by the uncertainty brought by linguistic expression.

5. Conclusion

It is difficult to directly solve the decision-making problems for energy systems prioritization especially under the conditions of hybrid information or missing information. MCDM methods provide a feasible way to prioritize energy systems, and the integration of MCDM and LCSA helps to analyse energy systems from a life-cycle sustainability perspective. However, few of the existing studies considered the hybrid data types in the decision-making problem. In the practice, the types of data are various since the difference in the data sources. To fill in this gap, this study defined three different hybrid data types and proposes a life cycle sustainability prioritization framework for the raking of energy systems from sustainability perspective based on the decision-making matrix with hybrid data types.

In this framework, a criteria system is established for sustainability assessment of energy systems, the best-worst method is employed to determine the weights of criteria and a novel MCDM model for decision-making under hybrid information is proposed for the sustainability prioritization of energy systems. This model consists of an innovative extension of grey relational analysis to solve decision-making problem with hybrid data types.

A case study regarding electricity generation was constructed for illustrating the proposed sustainability prioritization framework and evaluating the feasibility of the developed framework to achieve energy systems ranking with hybrid information.

The fuzzy GRA developed in the previous work of others, was applied to validate the results and evaluate the feasibility of the proposed method. Then, the sensitivity analysis was also conducted to investigate the robustness of the MCDM method under hybrid information proposed in this study. After the evaluations, the proposed method has been proven to be feasible for sustainability prioritization of energy systems under hybrid information. In addition, the accuracy and robustness of the proposed model have been investigated. And it could be concluded that the proposed approach is feasible for the decision-making problems with hybrid information or missing information.

The iGRA-MH model solves the decision making problem with missing information and hybrid information. However, the linguistic expressions, especially comparative linguistic terms, will definitely bring uncertainty and affect the accuracy of the results of the decision-making model. Some more complicated numerical expressions for uncertainty will be used in this method to improve the transformation accuracy of linguistic terms in the further study.

Acknowledgments

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