Hindawi
International Journal of Energy Research
Volume 2023, Article ID 8358799, 16 pages
https://doi.org/10.1155/2023/8358799

Research Article

Alleviating Energy Poverty through Renewable Energy Technology: An Investigation Using a Best-Worst Method-Based Quality Function Deployment Approach with Interval-Valued Intuitionistic Fuzzy Numbers

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Received 24 August 2022; Revised 10 October 2022; Accepted 28 October 2022; Published 3 February 2023

Academic Editor: Debabrata Barik

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Renewable energy technology is suitable for reducing energy consumption and emissions, and the corresponding impact on energy poverty has aroused tremendous attention. This paper proposed the best-worst method- (BWM-) based quality function deployment (QFD) approach within interval-valued intuitionistic fuzzy number (IVIFN) to select the appropriate renewable energy technology for energy poverty alleviation. QFD is firstly used to explore the relationship between energy poverty reduction requirements (CRs), renewable energy technology selection criteria (TRs), and correlation among TRs. Interval-valued intuitionistic fuzzy (IVIF) BWM is then applied for obtaining the correlation among CRs. After that, the IVIF-QFD method is used to attain the weight of TRs, which are then used to evaluate the renewable energy technology alternatives through IVIF-VIKOR approach. The six representative renewable energy technologies, including wind energy, solar energy, biomass (direct combustion, combined heat and power, and gasification), and hydropower have been selected in the decision model, and the result shows that the large-scale hydropower could be selected as the best choice to reduce the energy poverty issues, whose interval numbers is [0, 0.2925]. Except for prioritization of the selected technologies, findings of this paper could also contribute to developing sustainable renewable energy policies and energy roadmaps.

1. Introduction

Renewable energy (RE) developed rapidly among various energy resources all over the world and has been considered as having tremendous potential to benefit society [1]. It has been estimated that by 2050, solar and wind will provide more than 95% of energy and the corresponding expenditures would reduce from €51/MWh in 2015 to €53/MWh in 2050 [2]. Renewable energy resources can be a useful tool for realizing the electrification in far-flung villages [3], because these resources, such as wind, solar, and biomass, could produce electricity for people located in off-grid and remote areas to increase their living standards and contribute to the economy of the regions [4]. Meanwhile, the Russian-Ukraine crisis impels the EU to depend less on traditional fossil fuels and accelerate renewable energy development to satisfy energy consumption for survival [5]. Therefore, increasing renewable energy consumption could alleviate energy poverty (EP) all over the world [6]. EP is defined as the inaccessibility to clean energy and efficient facilities and deep reliance on traditional fossil fuels for cooking [7]. Around one billion people are having limited access to electricity, and most of them live in Africa [8]. At the same time, merely 50% of residents in Sub-Saharan Africa are electrified [9]. More specifically, besides developing countries, severe EP conditions have also been confirmed in developed countries, including Canada [10], Spain [11], and Germany [12]. Severe EP conditions have challenged worldwide energy systems, threatened sustainable development, and attracted various attentions, because it has done harm to health, caused gender inequality, and led to environmental pollution. In this background, countries have struggled with developing suitable renewable energy resources to alleviate EP [13]. Therefore, identifying appropriate renewable energy technology to effectively alleviate EP is a meaningful topic to be explored [14, 15].

In general, selecting renewable energy resources to alleviate EP is a typical multicriteria decision-making (MCDM) problem to be tackled by the MCDM method. Among various MCDM approaches, quality function deployment (QFD) is a useful tool to transform customer requirements (CRs) into technical features. QFD is capable of combining customer demands with technology characteristics quantitatively; in this way, the function of the selected technology is in accord with customer expectations [16, 17]. However, although QFD could transform customer demands into meaningful and practical action, the vagueness of customers' expectations and corresponding technical requirements (TRs) further complicate the problem [18].

In this study, to reflect the uncertainties of evaluation and display the diversities among different decision makers (DMs), QFD is combined with the interval-valued intuitionistic fuzzy (IVIF) sets to deal with the uncertainty in customers' EP alleviation demands for selecting the practical renewable energy technology. The proposed IVIF-QFD presents a comprehensive framework to display the relationship between various EP reduction expectations and corresponding TRs. Then, the IVIF best-worst method (BWM) is proposed to calculate each criterion weight of customer demands, because it can reflect uncertainty, vagueness, and subjective opinion from experts, and maximize the assessment accuracy [19]. After that, filling in the house of quality (HoQ) and calculating weights of all TRs enable DMs to focus on the most critical technical criteria [19]. However, it is insufficient to merely identify the most critical technical criteria; real-life problems require us to select the most suitable technology to directly alleviate EP. In this regard, a compromise method is needed to assist decision makers in achieving a final result with many contradictory criteria involved [20]. VIKOR approach could prioritize the alternatives and display the mutual concession between different alternatives [21]. Besides VIKOR, another MCDM technique such as technique for order preference by similarity to ideal solution (TOPSIS) [22] could also prioritize various alternatives. However, TOPSIS approach obtains the ranking result by considering the distance between negative and positive ideal solution, without any relative distances considered. From this point of view, IVIF-VIKOR is an appropriate compromise solution to show the mutual concession between different alternatives [20]. Therefore, IVIF-BWM and IVIF-VIKOR approaches are integrated into traditional QFD in this study, which improves the efficiency of dealing with complicated decision-making problems to provide a rational and practical result.

This paper aims at proposing an integrated model IVIF BWM-QFD-VIKOR for selecting renewable energy technology to reduce EP. Firstly, it uses interval-valued intuitionistic fuzzy numbers (IVIFNs) to improve the traditional fuzzy set by introducing membership and nonmembership functions and uncertainty degrees. After that, to better figure out the EP reduction expectations, IVIF-BWM is used to obtain the weight of each criterion by showing the vagueness and uncertainty during the decision-making process. Further, the IVIF-QFD method could accurately understand the relationship between EP reduction expectations and renewable energy technology requirements associated with them. This quantitative information ensures that the selected technical criteria could satisfy the EP reduction requirement. Finally, based on weights of technical criteria, the IVIF-VIKOR is used to prioritize alternatives by considering their mutual concession for identifying which renewable energy technology prioritizes over others for EP alleviation.

This paper is structured in the following sequence: Section 2 conducted the overview of EP and renewable energy technology; Section 3 involved the preliminary and specific stages for the proposed IVIF BWM-QFD-VIKOR approach; Section 4 used a case study to demonstrate a novel method in real life. The discussion is given in Section 5; conclusion of results and recommendations for further studies are presented in Section 6.

2. Literature Review

2.1. Energy Poverty and Renewable Energy Technology. EP is a relatively novel conception with tremendous implications [23, 24]. It is widely confirmed that limited access to modern energy has a severe socio-economic-environment impact [25], leading to health problems [26, 27], income inequality [28], and severe environmental issues [29, 30]. It is closely related to the quality of life of human beings and needs to be paid more and more attention for its alleviation [31].

Currently, the realization of EP reduction relies on accelerating transformations of energy structures, which means utilizing modern energy instead of fossil fuels [32]. By employing the subnational dataset of China, the low-carbon energy transition can significantly lead to EP alleviation by increasing energy service and clean energy consumption [32]. Using 2012, 2014, 2016, and 2018 data from China Family Panel Studies (CFPS), Hong et al. [33] empirically revealed that increasing clean energy consumption could reduce the chance of households suffering from EP. The rapid expansion of renewable energy industries could also help reduce reliance on fossil fuels and realize EP reduction [34]. Based on the Annual data from 2000 to 2014 of 64 countries all over the world, Zhao et al. [6] investigated the impact of renewable energy consumption on EP alleviation and revealed that renewable energy could alleviate global EP and improve energy efficiency. After investigating the 8239 households from 25 provinces of China, Wang et al. [35] found that renewable energy technology can significantly alleviate EP. More specifically, solar photovoltaic (PV), a representative RE, could increase energy access in regions, where accessing electricity is costly and difficult, to reduce EP [36, 37]. According to household-level data in Ghana, Obeng et al. [38] investigated the relationship between solar energy and poverty and discovered that solar PV could assist EP alleviation; Zubi et al. [39] also obtained similar findings. Other research explored that solar installation would decrease household electricity expenditure and improve EP [40, 41].

2.2. Renewable Energy Technology Selection and MCDM Methods. MCDM approach has been used in various energy problems, such as energy planning, energy resource allocation, and energy policy [42, 43]. For the complexity of the energy system and the multidimensional characteristics of sustainability, Mardani et al. [44] declared that different dimensions should be considered to make reasonable energy planning. Compared with a single criterion, the MCDM method could consider the various conflicting criteria to obtain integrated decision-making [45]. Therefore, to choose suitable renewable energy technology considering multiple-involved criteria comprehensively, MCDM technology is a suitable approach. Mardani et al. [44] overviewed 196 papers ranging from 1955 to 2015 related to energy planning and revealed that MCDM methods have been used in energy planning. For example, Lee and Chang [42] used four MCDM approaches—WSM, VIKOR, TOPSIS, and ELECTRE—to select renewable energy resources for electricity generation. Çolak and Kaya [46] proposed an integrated MCDM model, which combines the fuzzy analytic hierarchy process (FAHP) and fuzzy TOPSIS method to prioritize the renewable energy alternatives in Turkey. Sitorus and Brito-Parada [47] used the hybrid MCDM method to select renewable energy technologies by considering both subjective and objective multiple criteria. Ullah et al. [48] used an integrated model by combining fuzzy AHP, fuzzy TOPSIS, fuzzy EDAS, and fuzzy MOORA to plan the on/off grid hybrid renewable energy supply. Besides, fuzzy VIKOR [49] has also been applied in renewable energy source evaluation.

2.3. Research Gap. As mentioned above, plenty of studies have explored the relationship between EP and renewable energy technology and proposed the models to select the optimal renewable energy technology. However, some research gaps still need to be further discussed:

(i) Although scholars agree that it is necessary to use renewable energy to alleviate EP, most of the current research is about the influence of solar energy on EP alleviation. However, the impact of other renewable energy sources, such as wind, hydro, and biomass energy on EP reduction has not been explored. Consequently, the black box of the impact of main renewable energies on EP has not been fully opened yet and further research is urgently needed

(ii) Previous research mainly used hybrid methods for renewable energy technology selection; on the other hand, the customer requirement has not been considered in selecting the most suitable energy technology, which involves in the interaction between customer demands and technology requirements

This study fills these research gaps and proposes a framework to prioritize renewable energy technology for EP alleviation. This framework allows us to find out the solution for promoting renewable energy technology and identify which renewable energy technology prioritizes over others. The possible contributions of this study are as follows:

(i) It comprehensively considers the impact of six representative renewable energy technologies to discover their relationship with EP alleviation

(ii) It determines the weight of customer demand criterion with IVIF-BWM by considering not only the interaction among criteria but also the uncertainty and vagueness of the decision-making process

(iii) It transforms the customer demands into technical features with the IVIF-QFD for ensuring that the function of the selected technical criteria is in accord with customer expectations

3. Methodology

This paper proposes a new model by combining BWM, QFD, and VIKOR with IVIFNs to prioritize different alternatives. Even though intuitionistic fuzzy set (IFS) provides the DMs with functions of memberships and nonmemberships, interval-valued intuitionistic fuzzy set (IVIFS) is superior at coping with the complicated problem by equipping elements of these two functions at interval level [50]. Three stages have been included, as shown in Figure 1. In this study, we consider the CRs as EP reduction requirements and TRs as renewable energy technology selection criteria. In the first stage, the weight of CR (EP reduction) criteria in QFD is calculated by using IVIF-BWM. The next stage calculates the correlation among CRs and TRs (renewable energy technology selection criteria) in QFD, which are further combined with the weight of CRs to obtain the weight of TRs. These weights are finally used in stage 3 within the interval-valued intuitionistic fuzzy number- (IVIFN-) based VIKOR method to prioritize the appropriate renewable energy technology for EP alleviation.

3.1. Preliminary. In this section, a few fundamental conceptions of IFS and IVIFS have been presented.

Definition 1 see ([51]). Assume that $X=\{x_1, x_2, \cdots, x_n\}$ is a set. A fuzzy set A' in X is as follows:

$$A' = \{\langle x, \mu_{A'}(x) | x \in X\rangle\}. \tag{1}$$

Where $\mu_{A'} : X \longrightarrow [0, 1]$ is the membership function and $\mu_{A'}(x)$ is the membership degree of $x \in X$ to A'.

Definition 2 see ([52]). Assume that $X=\{x_1, x_2, \cdots, x_n\}$ is a set, an IFS A is:

$$A = \{\langle x, \mu_A(x), \nu_A(x) | x \in X\rangle\}. \tag{2}$$

Where $\mu_A(x)$ and $\nu_A(x)$ represent the membership degree and nonmembership degree of x to A, respectively, satisfying for all $x \in X$, $0 \le \mu_A(x) + \nu_A(x) \le 1$, and $\mu_A(x), \nu_A(x) \in [0, 1]$.

Definition 3 see ([52]). Let X be a nonempty set, an IVIFS $\tilde{A}$ is as follows:

$$\tilde{A} = \{\langle x, \tilde{\mu}_{\tilde{A}}(x), \tilde{v}_{\tilde{A}}(x) | x \in X\rangle\}. \quad (3)$$

Where $\tilde{\mu}_{\tilde{A}}(x) = [\mu^L_{\tilde{A}}, \mu^U_{\tilde{A}}] \subset [0, 1]$ and $\tilde{v}_{\tilde{A}}(x) = [v^L_{\tilde{A}}, v^U_{\tilde{A}}] \subset [0, 1]$ are membership interval and nonmembership interval of $x \in X$ to $\tilde{A}$, respectively, satisfying $\max \tilde{\mu}_{\tilde{A}}(x) + \max \tilde{v}_{\tilde{A}}(x) \leq 1, \forall x \in X$. $\pi_{\tilde{A}}(x) = [\pi^L_{\tilde{A}}, \pi^U_{\tilde{A}}]$ is the hesitation interval of x to A, where $\pi^L_{\tilde{A}} = 1 - \mu^U_{\tilde{A}} - v^U_{\tilde{A}}$, $\pi^U_{\tilde{A}} = 1 - \mu^L_{\tilde{A}} - v^L_{\tilde{A}}$.

Definition 4 see ([53]). Suppose that

$$\begin{aligned} A &= \left\{\left\langle x_i\left[\mu^L_{\tilde{A}}(x_i), \mu^U_{\tilde{A}}(x_i)\right], \left[v^L_{\tilde{A}}(x_i), v^U_{\tilde{A}}(x_i)\right]\right\rangle | x_i \in X\right\}, \\ B &= \left\{\left\langle x_i\left[\mu^L_{\tilde{B}}(x_i), \mu^U_{\tilde{B}}(x_i)\right], \left[v^L_{\tilde{B}}(x_i), v^U_{\tilde{B}}(x_i)\right]\right\rangle | x_i \in X\right\}, \end{aligned} \quad (4)$$

then the basic arithmetic is defined in the following formulas:

$$\begin{aligned} A + B &= \left\{\left\langle x_i\left[\mu^L_{\tilde{A}}(x_i), \mu^U_{\tilde{A}}(x_i)\right], \left[v^L_{\tilde{A}}(x_i), v^U_{\tilde{A}}(x_i)\right]\right\rangle | x_i \in X\right\} \\ &\quad + \left\{\left\langle x_i\left[\mu^L_{\tilde{B}}(x_i), \mu^U_{\tilde{B}}(x_i)\right], \left[v^L_{\tilde{B}}(x_i), v^U_{\tilde{B}}(x_i)\right]\right\rangle | x_i \in X\right\} \\ &= \left\{\left\langle \begin{array}{c} x_i\left[\mu^L_{\tilde{A}}(x_i) + \mu^L_{\tilde{B}}(x_i) - \mu^L_{\tilde{A}}(x_i) \cdot \mu^L_{\tilde{B}}(x_i), \mu^U_{\tilde{A}}(x_i) + \mu^U_{\tilde{B}}(x_i) - \mu^U_{\tilde{A}}(x_i) \cdot \mu^U_{\tilde{B}}(x_i)\right], \\ \left[v^L_{\tilde{A}}(x_i) \cdot v^L_{\tilde{B}}(x_i), v^U_{\tilde{A}}(x_i) \cdot v^U_{\tilde{B}}(x_i)\right] \end{array} \right\rangle | x_i \in X\right\}, \\ A - B &= \left\{\left\langle x_i\left[\mu^L_{\tilde{A}}(x_i), \mu^U_{\tilde{A}}(x_i)\right], \left[v^L_{\tilde{A}}(x_i), v^U_{\tilde{A}}(x_i)\right]\right\rangle | x_i \in X\right\} \\ &\quad - \left\{\left\langle x_i\left[\mu^L_{\tilde{B}}(x_i), \mu^U_{\tilde{B}}(x_i)\right], \left[v^L_{\tilde{B}}(x_i), v^U_{\tilde{B}}(x_i)\right]\right\rangle | x_i \in X\right\} \\ &= \left\{\left\langle \begin{array}{c} x_i\left[\mu^L_{\tilde{A}}(x_i) \cdot v^L_{\tilde{B}}(x_i), \mu^U_{\tilde{A}}(x_i) \cdot v^U_{\tilde{B}}(x_i)\right], \\ \left[v^L_{\tilde{A}}(x_i) + \mu^L_{\tilde{B}}(x_i) - v^L_{\tilde{A}}(x_i) \cdot \mu^L_{\tilde{B}}(x_i), v^U_{\tilde{A}}(x_i) \cdot v^U_{\tilde{B}}(x_i), v^U_{\tilde{A}}(x_i) \cdot v^U_{\tilde{B}}(x_i)\right] \end{array} \right\rangle | x_i \in X\right\}, \\ A \cdot B &= \left\{\left\langle x_i\left[\mu^L_{\tilde{A}}(x_i), \mu^U_{\tilde{A}}(x_i)\right], \left[v^L_{\tilde{A}}(x_i), v^U_{\tilde{A}}(x_i)\right]\right\rangle | x_i \in X\right\} \\ &\quad \cdot \left\{\left\langle x_i\left[\mu^L_{\tilde{B}}(x_i), \mu^U_{\tilde{B}}(x_i)\right], \left[v^L_{\tilde{B}}(x_i), v^U_{\tilde{B}}(x_i)\right]\right\rangle | x_i \in X\right\} \\ &= \left\{\left\langle \begin{array}{c} x_i\left[\mu^L_{\tilde{A}}(x_i) \cdot \mu^L_{\tilde{B}}(x_i), \mu^U_{\tilde{A}}(x_i) \cdot \mu^U_{\tilde{B}}(x_i)\right], \\ \left[v^L_{\tilde{A}}(x_i) + v^L_{\tilde{B}}(x_i) - v^L_{\tilde{A}}(x_i) \cdot v^L_{\tilde{B}}(x_i), v^U_{\tilde{A}}(x_i) + v^U_{\tilde{B}}(x_i) - v^U_{\tilde{A}}(x_i) \cdot v^U_{\tilde{B}}(x_i)\right] \end{array} \right\rangle | x_i \in X\right\}, \\ \frac{A}{B} &= \frac{\left\{\left\langle x_i\left[\mu^L_{\tilde{A}}(x_i), \mu^U_{\tilde{A}}(x_i)\right], \left[v^L_{\tilde{A}}(x_i), v^U_{\tilde{A}}(x_i)\right]\right\rangle | x_i \in X\right\}}{\left\{\left\langle x_i\left[\mu^L_{\tilde{B}}(x_i), \mu^U_{\tilde{B}}(x_i)\right], \left[v^L_{\tilde{B}}(x_i), v^U_{\tilde{B}}(x_i)\right]\right\rangle | x_i \in X\right\}} \cdot \\ &= \left\{\left\langle \begin{array}{c} x_i\left[\mu^L_{\tilde{A}}(x_i) + v^L_{\tilde{B}}(x_i) - \mu^L_{\tilde{A}}(x_i) \cdot v^L_{\tilde{B}}(x_i), \mu^U_{\tilde{A}}(x_i) + v^U_{\tilde{B}}(x_i) - \mu^U_{\tilde{A}}(x_i) \cdot v^U_{\tilde{B}}(x_i)\right], \\ \left[v^L_{\tilde{A}}(x_i) \cdot \mu^L_{\tilde{B}}(x_i), v^U_{\tilde{A}}(x_i) \cdot \mu^U_{\tilde{B}}(x_i)\right. \end{array} \right\rangle | x_i \in X\right\}. \end{aligned} \quad (5)$$

Definition 5 see ([54]). $\tilde{a} = ([a, b], [c, d])$ is an IVIFN, with the following condition: $0 \leq a \leq b \leq 1$, $0 \leq c \leq d \leq 1$, and $b + d \leq 1$. The score function $S(\tilde{a})$ and the accuracy function $H(\tilde{a})$ of $\tilde{a}$ are expressed in the following formulas:

$$S(\tilde{a}) = \frac{a + b - c - d}{2}, \quad (6)$$

$$H(\tilde{a}) = \frac{a + b + c + d}{2}. \quad (7)$$

Definition 6 see ([55]). Let $\tilde{a}_1 = ([a_1, b_1], [c_1, d_1])$ and $\tilde{a}_2 = ([a_2, b_2], [c_2, d_2])$ be two IVIFNs and comparisons are as follows:

(1) If $S(\tilde{a}_1) > S(\tilde{a}_2)$, then $\tilde{a}_1 > \tilde{a}_2$

(2) If $S(\tilde{a}_1) = S(\tilde{a}_2)$, then

(a) If $H(\tilde{a}_1) > H(\tilde{a}_2)$, then $\tilde{a}_1 > \tilde{a}_2$

(b) If $H(\tilde{a}_1) = H(\tilde{a}_2)$, then $\tilde{a}_1 = \tilde{a}_2$

Definition 7 see ([56]). Assume that $\tilde{a}_1 = ([a_1, b_1], [c_1, d_1])$ and $\tilde{a}_2 = ([a_2, b_2], [c_2, d_2])$ are IVIFNs, and the Hamming distance is:

$$D_H(\tilde{a}_1, \tilde{a}_2) = \frac{1}{4}(|a_1 - a_2| + |b_1 - b_2| + |c_1 - c_2| + |d_1 - d_2|). \quad (8)$$

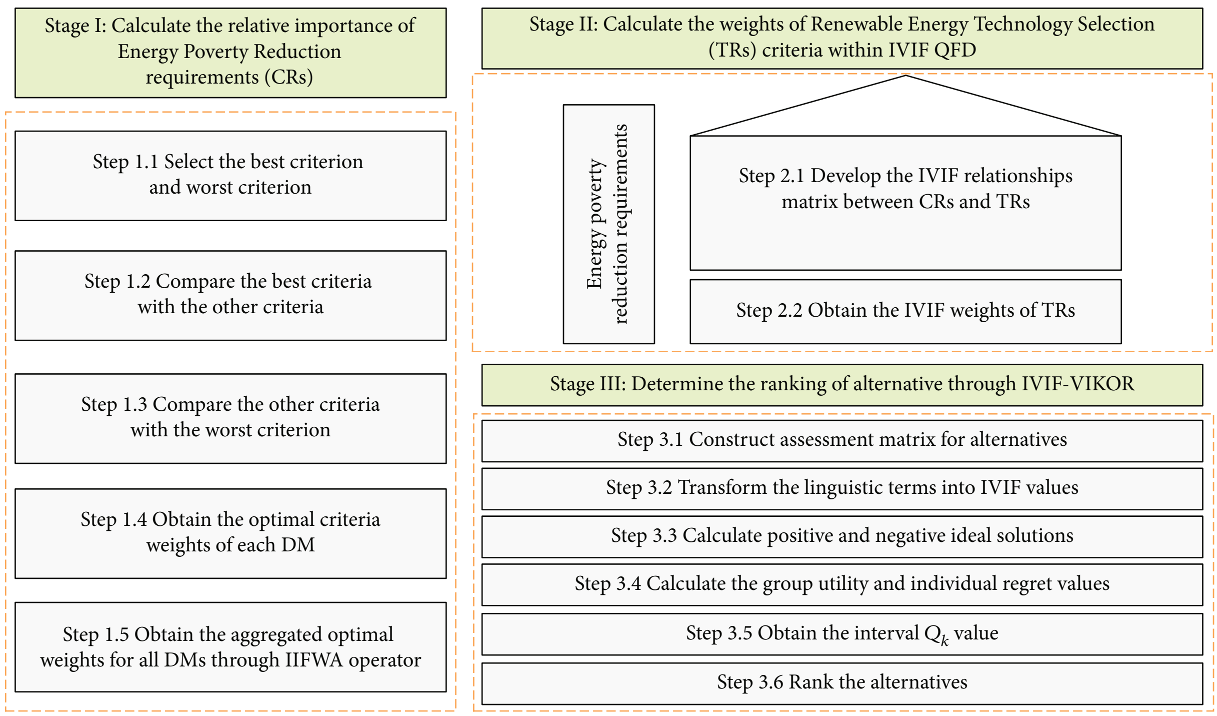

Figure 1: Flowchart of the methodology.

Definition 8 see ([57]). Let $\tilde{a}_i = ([a_i, b_i], [c_i, d_i])(i = 1, 2, \cdots, n)$ be IVIFNs and interval-valued intuitionistic fuzzy-weighted averaging (IIFWA) is the IVIF-weighted averaging operator. IIFWA : $R^n \longrightarrow R$, where R is the set of IVIFNs, $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_n)^T$ is the weight vector of $\tilde{a}_i$ with $\sum_{i=1}^{n} \lambda_i = 1$. Then, aggregated IVIFN value is expressed in the following formula:

$$\mathrm{IIFWA}_\lambda(\tilde{a}_1, \tilde{a}_2, \cdots, \tilde{a}_n) = \lambda_1 \tilde{a}_1 \oplus \lambda_2 \tilde{a}_2 \oplus \cdots \oplus \lambda_n \tilde{a}_n. \quad (9)$$

Equation (9) could be transformed into the following formula:

$$\begin{aligned}&\mathrm{IIFWA}_\lambda(\tilde{a}_1, \tilde{a}_2, \cdots, \tilde{a}_n)\\&= \left(\left[1 - \prod_{i=1}^{n} (1 - a_i)^{\lambda_i}, 1 - \prod_{i=1}^{n} (1 - b_i)^{\lambda_i}\right], \left[\prod_{i=1}^{n} (c_i)^{\lambda_i}, \prod_{i=1}^{n} (d_i)^{\lambda_i}\right]\right).\end{aligned} \quad (10)$$

3.2. A Proposed Model. The proposed model combines BWM, QFD, and VIKOR with IVIFNs to prioritize the evaluated alternatives. Firstly, the IVIF-BWM is proposed to calculate the weight of CR criteria, by considering the vagueness and uncertainty of experts and interaction among criteria. Then, the correlations among CRs and TRs are obtained through IVIF-QFD. After that, by combining the correlation coefficient and CR weights, the TR weights are calculated. Finally, TR weights are applied in Stage 3 through IVIF-VIKOR approach to rank the different renewable energy technologies for EP alleviation.

$C = (C_1, C_2, \cdots, C_n)$ is criterion set. DM_k is k_{th} expert with the weight of each expert being expressed as $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_l)^T$, $\sum_{k=1}^{l} \lambda_k = 1$, and $0 < \lambda_k < 1$.

Stage 1. Calculate the relative importance of energy poverty reduction requirements (CRs).

Five steps are involved in the IVIF-BWM approach [19]:

Step 1. Select the best criterion and the worst criterion. The selection process is up to experts' opinions.

Step 2. Compare the best criterion with other criteria. Best-to-others vector is evaluated by DM_k in the following formula [19]:

$$\tilde{R}_B^{(k)} = \left(\tilde{r}_{B1}^{(k)}, \tilde{r}_{B2}^{(k)}, \cdots, \tilde{r}_{\mathrm{Bn}}^{(k)}\right). \quad (11)$$

Where $\tilde{r}_{\mathrm{Bj}}^{(k)} = ([\tilde{\mu}_{\mathrm{Bj}}^L, \tilde{\mu}_{\mathrm{Bj}}^U], [\tilde{\nu}_{\mathrm{Bj}}^L, \tilde{\nu}_{\mathrm{Bj}}^U])^{(k)}$ denotes the IVIF degree of the best criterion C_B over the criterion C_j given the k_{th} decision maker (DM).

Step 3. Compare the other criteria with the worst criterion. Other-to-worst vector is assessed by DM_k in the following formula [19]:

$$\tilde{R}_W^{(k)} = \left(\tilde{r}_{1W}^{(k)}, \tilde{r}_{2W}^{(k)}, \cdots, \tilde{r}_{\mathrm{nW}}^{(k)}\right). \quad (12)$$

Where $\tilde{r}_{\mathrm{jW}}^{(k)} = ([\tilde{\mu}_{\mathrm{jW}}^L, \tilde{\mu}_{\mathrm{jW}}^U], [\tilde{\nu}_{\mathrm{jW}}^L, \tilde{\nu}_{\mathrm{jW}}^U])^{(k)}$ denotes the IVIF degree of criterion C_j over the worst criterion C_W given k_{th} DM.

Step 4. Obtain the optimal criteria weights of each DM.

Suppose $\tilde{\omega}_B^{(k)} = ([\mu_B^L, \mu_B^U], [\nu_B^L, \nu_B^U])^{(k)}, \tilde{\omega}_W^{(k)} = ([\mu_W^L, \mu_W^U], [\nu_W^L, \nu_W^U])^{(k)}, \tilde{\omega}_j^{(k)} = ([\mu_j^L, \mu_j^U], [\nu_j^L, \nu_j^U])^{(k)}$ The optimal weight should satisfy that, for each pair of $\tilde{\omega}_B^{(k)}/\tilde{\omega}_j^{(k)}$ and $\tilde{\omega}_j^{(k)}/\tilde{\omega}_W^{(k)}$, we have $|(\tilde{\omega}_B^{(k)}/\tilde{\omega}_W^{(k)}) - \tilde{r}_{\mathrm{Bj}}^{(k)}|$ and $|(\tilde{\omega}_j^{(k)}/\tilde{\omega}_W^{(k)}) - \tilde{r}_{\mathrm{jW}}^{(k)}|$ with all C_j being minimized. The optimal criteria weights of each DM are obtained by solving the following equation [19]:

$$
\begin{gathered}
\min \varepsilon, \\
s.t., \\
\left| \mu_B^{L(k)} + \nu_j^{L(k)} - \mu_B^{L(k)} \cdot \nu_j^{L(k)} - \mu_{\mathrm{Bj}}^{L\,(k)} \right| \le \varepsilon, \text{for all } C_j, \\
\left| \mu_B^{U(k)} + \nu_j^{U(k)} - \mu_B^{U(k)} \cdot \nu_j^{U(k)} - \mu_{\mathrm{Bj}}^{U\,(k)} \right| \le \varepsilon, \text{for all } C_j, \\
\left| \nu_B^{L\,(k)} + \mu_j^{L\,(k)} - \nu_{\mathrm{Bj}}^{L\,(k)} \right| \le \varepsilon, \text{for all } C_j, \\
\left| \nu_B^{U\,(k)} + \mu_j^{U\,(k)} - \nu_{\mathrm{Bj}}^{U\,(k)} \right| \le \varepsilon, \text{for all } C_j, \\
\left| \mu_j^{L(k)} + \nu_W^{L\,(k)} - \mu_j^{L(k)} \cdot \nu_W^{L\,(k)} - \mu_{\mathrm{jW}}^{L\,(k)} \right| \le \varepsilon, \text{for all } C_j, \\
\left| \mu_j^{U(k)} + \nu_W^{U\,(k)} - \mu_j^{U(k)} \cdot \nu_W^{U\,(k)} - \mu_{\mathrm{jW}}^{U\,(k)} \right| \le \varepsilon, \text{for all } C_j, \\
\left| \nu_j^{L(k)} + \mu_W^{L\,(k)} - \nu_{\mathrm{jW}}^{L\,(k)} \right| \le \varepsilon, \text{for all } C_j, \\
\left| \nu_j^{U(k)} + \mu_W^{U\,(k)} - \nu_{\mathrm{jW}}^{U\,(k)} \right| \le \varepsilon, \text{for all } C_j, \\
\sum_{j=1}^{n} S\left(\tilde{\omega}_j^{(k)}\right) = 1, \\
S\left(\tilde{\omega}_j^{(k)}\right) \ge 0, \text{for all } C_j.
\end{gathered} \tag{13}
$$

After solving Equation (13), the optimal weights $\tilde{\omega}^{(k)} = (\tilde{\omega}_1, \tilde{\omega}_2, \cdots, \tilde{\omega}_n)^{(k)}$ and ε^* with k_{th} DM are obtained. The value of ε^* is closer to zero, showing the higher pairwise comparison consistency [58].

Step 5. Obtain the aggregated optimal weights of all DMs through IIFWA operator [57].

The aggregated optimal weight of criteria $\tilde{\omega} = (\tilde{\omega}_1, \tilde{\omega}_2, \cdots, \tilde{\omega}_n)$ can be calculated in the following formula [57]:

$$
\begin{aligned}
&\mathrm{IIFWA}_\lambda\left(\tilde{\omega}_j^{(1)}, \tilde{\omega}_j^{(2)}, \cdots, \tilde{\omega}_j^{(l)}\right) \\
&\quad = \left(\left[1 - \prod_{k=1}^{l}\left(1 - \mu_j^{L(k)}\right)^{\lambda_k}, 1 - \prod_{k=1}^{l}\left(1 - \mu_j^{U(k)}\right)^{\lambda_k}\right]\right. \\
&\quad \left., \left[\prod_{k=1}^{l}\left(\nu_j^{L(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(\nu_j^{U(k)}\right)^{\lambda_k}\right]\right), \quad j = 1, 2, \cdots, n.
\end{aligned} \tag{14}
$$

The score of each $\tilde{\omega}_j$ can be obtained and the crisp weight number of each criterion is shown in the following

Table 1: Linguistic scale and corresponding IVIFNs [57].

Linguistic variable	Membership and nonmembership degrees
Absolutely low (AL)	([0, 0.2], [0.5, 0.8])
Very low (VL)	([0.1, 0.3], [0.4, 0.7])
Low (L)	([0.2, 0.4], [0.3, 0.6])
Medium low (ML)	([0.3, 0.5], [0.2, 0.5])
Approximately equal (AE)	([0.4, 0.6], [0.2, 0.4])
Medium high (MH)	([0.5, 0.7], [0.1, 0.3])
High (H)	([0.6, 0.8], [0, 0.2])
Very high (VH)	([0.7, 0.9], [0, 0.1])
Absolutely high (AH)	([0.8, 1.0], [0, 0])

equation:

$$
\omega_j = \frac{S(\tilde{\omega}_j)}{\sum_{j=1}^{n} S(\tilde{\omega}_j)}, \quad j = 1, 2, \cdots, n. \tag{15}
$$

Stage 2. Calculate the weights of renewable energy technology selection (TR) criteria within IVIF-QFD.

This phase includes 2 steps to build the QFD [59]. These steps indicate how renewable energy requirements (TRs) affect the EP reduction requirements (CRs) and consist of the relationships existing between CRs and TRs under the IVIF environment. The following steps calculate the absolute weights of TRs.

Step 1. Develop the IVIF relationship matrix between CRs and TRs on QFD. Experts express their judgments on the correlation matrix between CRs and TRs using IVIFNs given in Table 1.

Step 2. Obtain IVIF weights of TRs. The main contribution of IVIF-QFD is to determine which TRs are of critical importance to satisfy the CRs. The absolute weights of TRs are then calculated by integrating both the absolute weight of CRs and the relationship matrix.

To obtain the IVIF weights of TRs, IVIF weights of CRs (ω_j) are multiplied by IVIF relationships $(\tilde{R}_{\mathrm{Ji}})$ through Equation (16) [59].

$$
\mathrm{TW}_i = \sum_j \omega_j{}^* \tilde{R}_{\mathrm{Ji}}, \quad j = 1, 2, \cdots, n, i = 1, 2, \cdots, m. \tag{16}
$$

Where $\tilde{R}_{\mathrm{Ji}}$ denotes the fuzzy relationship matrix between CRs and TRs; $\tilde{\omega}_j$ denotes the weight of CRs; TW_i indicates the total weight of TRs.

Each IVIF weight of TRs has been divided by the total IVIF weights of TRs for calculating the normalized IVIF weight of TRs as in Equation (17) [59].

$$
N(\mathrm{TW}_i) = \frac{S(\mathrm{TW}_i)}{\sum_{i=1}^{m} S(\mathrm{TW}_i)}. \tag{17}
$$

Where $N(\mathrm{TW_i})$ is the normalized IVIF weight of TRs.

Table 2: Comparison of interval numbers [61].

Minimum interval number between $[a^L, a^U]$ and $[b^L, b^U]$	
When $a^U < b^L \Rightarrow$	$[a^L,\ a^U] < [b^L, b^U]$
When $a^L < b^L < b^U < a^U$, if $\alpha(b^L - a^L) \geq (1-\alpha)(a^U - b^U) \Rightarrow$	$[a^L, a\ U] < [b^L,\ b^U]$
When $a^L < b^L < b^U < a^U$, if $\alpha(b^L - a^L) < (1-\alpha)(a^U - b^U) \Rightarrow$	$[b^L, b^U] < [a^L, a^U]$
When $a^L < b^L < a^U < b^U$, if $\alpha(b^L - a^L) \geq (1-\alpha)(b^U - a^U) \Rightarrow$	$[a^L, a^U] < [b^L,\ b^U]$
When $a^L < b^L < a^U < b^U$, if $\alpha(b^L - a^L) < (1-\alpha)(b^U - a^U) \Rightarrow$	$[b^L,\ b^U] < [a^L, a^U]$

Stage 3. Determine the ranking of alternatives through IVIF-VIKOR.

Six steps are involved in the application of IVIF-VIKOR [60, 61].

Step 1. Construct assessment matrix for alternatives. Obtain the hybrid evaluation for the alternatives, from which the qualitative criteria use the linguistic terms as shown in Table 1 and quantitative criteria use interval value.

Step 2. Transform linguistic terms into IVIF values. The IVIF value is used to construct the group decision matrix ($\tilde{X}$), which includes p alternatives and m criteria. $\tilde{X}$ is defined as

$$\tilde{x}_{ki} = \left[\mu^L_{\tilde{A}}(\tilde{x}_{ki}), \mu^U_{\tilde{A}}(\tilde{x}_{ki})\right], \left[\nu^L_{\tilde{A}}(\tilde{x}_{ki}), \nu^U_{\tilde{A}}(\tilde{x}_{ki})\right]. \quad (18)$$

Where $k = 1, 2, \cdots, p$ and $i = 1, 2, \cdots, m$.

For interval values, f_{ki} is the evaluation of k_{th} alternative concerning i_{th} criterion and is not an exact number, known as $f_{ki} \in [f^L_{ki}, f^U_{ki}]$.

Step 3. Calculate the positive and negative ideal solutions. The positive and negative ideal solutions for IVIFNs are $\tilde{f}^*_i$ in Equation (19) and $\tilde{f}^-_i$ in Equation (20) [60], and for interval values are f^* in Equation (21) and f^- in Equation (22) [61], respectively.

$$\tilde{f}^*_i = \left[\mu^L_{\tilde{A}}(\tilde{x}^*_i), \mu^U_{\tilde{A}}(\tilde{x}^*_i)\right], \left[\nu^L_{\tilde{A}}(\tilde{x}^*_i), \nu^U_{\tilde{A}}(\tilde{x}^*_i)\right]. \quad (19)$$

Where $[\mu^L_{\tilde{A}}(\tilde{x}^*_i) = \max_k(\mu^L_{\tilde{A}}(\tilde{x}_{ki})), \mu^U_{\tilde{A}}(\tilde{x}^*_i) = \max_k(\mu^U_{\tilde{A}}(\tilde{x}_{ki}))]$, $[\nu^L_{\tilde{A}}(\tilde{x}^*_i) = \max_k(\nu^L_{\tilde{A}}(\tilde{x}_{ki})), \nu^U_{\tilde{A}}(\tilde{x}^*_i) = \max_k(\nu^U_{\tilde{A}}(\tilde{x}_{ki}))]$ and

$$\tilde{f}^-_i = \left[\mu^L_{\tilde{A}}(\tilde{x}^-_i), \mu^U_{\tilde{A}}(\tilde{x}^-_i)\right], \left[\nu^L_{\tilde{A}}(\tilde{x}^-_i), \nu^U_{\tilde{A}}(\tilde{x}^-_i)\right]. \quad (20)$$

Where $[\mu^L_{\tilde{A}}(\tilde{x}^-_i) = \max_k(\mu^L_{\tilde{A}}(\tilde{x}_{ki})), \mu^U_{\tilde{A}}(\tilde{x}^-_i) = \max_k(\mu^U_{\tilde{A}}(\tilde{x}_{ki}))]$, $[\nu^L_{\tilde{A}}(\tilde{x}^-_i) = \max_k(\nu^L_{\tilde{A}}(\tilde{x}_{ki})), \nu^U_{\tilde{A}}(\tilde{x}^-_i) = \max_k(\nu^U_{\tilde{A}}(\tilde{x}_{ki}))]$

$$f^* = \{f^*_1, \cdots, f^*_m\} = \left\{\left(\max_k f^U_{ki} | i \in J\right) \text{ or } \left(\max_k f^L_{ki} | i \in J\right)\right\} i = 1, 2, \cdots, m, \quad (21)$$

$$f^- = \{f^-_1, \cdots, f^-_m\} = \left\{\left(\max_k f^L_{ki} | i \in J\right) \text{ or } \left(\max_k f^U_{ki} | i \in J\right)\right\} i = 1, 2, \cdots, m. \quad (22)$$

Where I is benefit criterion and J is cost criterion.

Step 4. Calculate the group utility and individual regret values. The group utility values and individual regret values for IVIFN are $S(A_k)$ in Equation (23) and $R(A_k)$ in Equation (24), and for interval value are $[S^L_k, S^U_k]$ in Equations (26) and (27) and $[R^L_k, R^U_k]$ in Equations (28) and (29) [61], respectively.

$$S(A_k) = \sum_{i=1}^{m} \left[N(\mathrm{TW}_i) \frac{d\left(\tilde{f}^*_i, \tilde{x}_{ki}\right)}{d\left(\tilde{f}^*_i, \tilde{f}^-_i\right)}\right], \quad (23)$$

$$R(A_k) = \max_i \left[N(\mathrm{TW}_i) \frac{d\left(\tilde{f}^*_i, \tilde{x}_{ki}\right)}{d\left(\tilde{f}^*_i, \tilde{f}^-_i\right)}\right], \quad (24)$$

where

$$d\left(\tilde{f}^*_i, \tilde{x}_{ki}\right) = \frac{1}{4}\begin{pmatrix} \left|\mu^L_{\tilde{A}}(\tilde{x}^*_i) - \mu^L_{\tilde{A}}(\tilde{x}_{ki})\right| + \left|\mu^U_{\tilde{A}}(\tilde{x}^*_i) - \mu^U_{\tilde{A}}(\tilde{x}_{ki})\right| \\ + \left|\nu^L_{\tilde{A}}(\tilde{x}^*_i) - \nu^L_{\tilde{A}}(\tilde{x}_{ki})\right| + \left|\nu^U_{\tilde{A}}(\tilde{x}^*_i) - \nu^U_{\tilde{A}}(\tilde{x}_{ki})\right| \\ + \left|\pi^L_{\tilde{A}}(\tilde{x}^*_i) - \pi^L_{\tilde{A}}(\tilde{x}_{ki})\right| + \left|\pi^U_{\tilde{A}}(\tilde{x}^*_i) - \pi^U_{\tilde{A}}(\tilde{x}_{ki})\right| \end{pmatrix},,$$

$$d\left(\tilde{f}^*_i, \tilde{f}^-_i\right) = \frac{1}{4}\begin{pmatrix} \left|\mu^L_{\tilde{A}}(\tilde{x}^*_i) - \mu^L_{\tilde{A}}(\tilde{x}^-_i)\right| + \left|\mu^U_{\tilde{A}}(\tilde{x}^*_i) - \mu^U_{\tilde{A}}(\tilde{x}^-_i)\right| \\ + \left|\nu^L_{\tilde{A}}(\tilde{x}^*_i) - \nu^L_{\tilde{A}}(\tilde{x}^-_i)\right| + \left|\nu^U_{\tilde{A}}(\tilde{x}^*_i) - \nu^U_{\tilde{A}}(\tilde{x}^-_i)\right| \\ + \left|\pi^L_{\tilde{A}}(\tilde{x}^*_i) - \pi^L_{\tilde{A}}(\tilde{x}^-_i)\right| + \left|\pi^U_{\tilde{A}}(\tilde{x}^*_i) - \pi^U_{\tilde{A}}(\tilde{x}^-_i)\right| \end{pmatrix}. \quad (25)$$

Computing $[S^L_k, S^U_k]$ and $[R^L_k, R^U_k]$ interval as below:

$$S^L_k = \sum_{i \in I} N(\mathrm{TW}_i)\left(\frac{f^*_i - f^U_{ki}}{f^*_i - f^-_i}\right) + \sum_{i \in J} N(\mathrm{TW}_i)\left(\frac{f^L_{ki} - f^*_i}{f^-_i - f^*_i}\right) k = 1, \cdots, p, \quad (26)$$

Table 3: Renewable energy plant characteristics [65, 67–69].

	Economical			Technical			Social		Environment	
	Initial investment (USD/kW) TR11	Annual operation and maintenance cost (USD/kW-year) TR12	Service life TR13	Technology maturity TR21	Efficiency/ capacity factor (%) TR22	Reliability TR23	Job creation (jobs/MW) TR31	Social impact TR32	Land requirement (m^2/GWh) TR41	Emission (kg CO_2-eq/MWh) TR42
Wind energy	1200-2100	46	20	High	20-40	Nondispatchable	12.2	Minor	1030-2780	5-35
Solar energy	2700-6800	14-69	20	Medium	12-21	Nondispatchable	20.2	Medium	164-552	40-160
Direct combustion	1880-4260	84	20	High	85	Dispatchable	13.2	Minor	193	8.5-118
CHP	3550-6820	54-86	25	Medium	63-74	Dispatchable	13.2	Minor	175	25-130
Gasification	2140-5700	65-71	20-25	Medium	80	Dispatchable	13.2	Minor	126	17-117
Hydropower	1400-4150	25-75	35	High	17-59	Dispatchable	7.8-22.9	Medium	2350-25000	2-40
Type	Cost	Cost	Benefit	Benefit	Benefit	Benefit	Benefit	Benefit	Cost	Cost

$$S_k^U = \sum_{i\in I} N(\mathrm{TW}_i)\left(\frac{f_i^* - f_{\mathrm{ki}}^L}{f_i^* - f_i^-}\right) + \sum_{i\in J} N(\mathrm{TW})_i\left(\frac{f_{\mathrm{ki}}^U - f_i^*}{f_i^- - f_i^*}\right) k = 1, \cdots, p, \tag{27}$$

$$R_k^L = \max\left\{N(\mathrm{TW_i})\left(\frac{f_i^* - f_{\mathrm{ki}}^U}{f_i^* - f_i^-}\right)\middle| i\in I, N(\mathrm{TW}_i)\left(\frac{f_{\mathrm{ki}}^L - f_i^*}{f_i^- - f_i^*}\right)\middle| i\in J\right\} k = 1, \cdots, p, \tag{28}$$

$$R_k^U = \max\left\{N(\mathrm{TW}_i)\left(\frac{f_i^* - f_{\mathrm{ki}}^L}{f_i^* - f_i^-}\right)\middle| i\in I, N(\mathrm{TW}_i)\left(\frac{f_{\mathrm{ki}}^U - f_i^*}{f_i^- - f_i^*}\right)\middle| i\in J\right\} k = 1, \cdots, p, \tag{29}$$

where $N(\mathrm{TW_i})$ is weight of the criterion C_i.

Step 5. Obtain interval $Q_k = [Q_k^L, Q_k^U]$; $k = 1, 2, \cdots, p$, by following equations [60, 61]:

$$Q_k^L = v\frac{(S_k^L - S^*)}{(S^- - S^*)} + (1-v)\frac{(R_k^L - R^*)}{(R^- - R^*)}, \tag{30}$$

$$Q_k^U = v\frac{(S_k^U - S^*)}{(S^- - S^*)} + (1-v)\frac{(R_k^U - R^*)}{(R^- - R^*)}. \tag{31}$$

Where

$$\begin{aligned} S^* &= \min_k S_k^L,\ S^- = \max_k S_k^U, \\ R^* &= \min_k R_k^L,\ R^- = \max_k R_k^U. \end{aligned} \tag{32}$$

v is the weight of the maximum group utility, here let $v = 0.5$.

Step 6. Rank the alternatives. Based on the VIKOR method, the alternative with minimum $Q_k([Q_k^L, Q_k^U])$ ranks first and is selected as the compromise result. $Q_k, k = 1, \cdots, p$ are interval numbers and the corresponding comparison rules are presented in Table 2. The parameter $\alpha(0 < \alpha \le 1)$ is the optimal level of DM, with rational DM $\alpha = 0.5$.

4. Case Study

The case study is used to illustrate multicriteria assessment of renewable energy technology for EP alleviation to examine the feasibility of the proposed IVIF BWM-QFD-VIKOR approach and to explore how the proposed integrated method is applied in real life.

4.1. Case Study Description of the Renewable Energy Technology for EP Alleviation. The rapid expansion of renewable energy industries could help reduce reliance on fossil fuels in daily life and realize the target of carbon emission reduction [34]. Appropriate usage of renewable energy resources could benefit electricity production. Nevertheless, barriers, including technical, economic, environmental, and social factors, challenge the development of renewable energy technology [62]. Selecting the suitable renewable energy resource is one key barrier to realizing EP alleviation, and limited method exists for solving the problem [3]. This is a complicated decision-making problem with many technical, economic, environmental, and social issues considered. Therefore, this paper contributes to selecting the optimal renewable energy technology for EP alleviation by using the proposed MCDM method.

Table 4: The best and the worst criteria.

DM	The best evaluation criterion	The worst evaluation criterion
DM1	CR2	CR4
DM2	CR3	CR5
DM3	CR1	CR5

Table 5: Linguistic terms for pair-wise comparison of criteria [19].

Linguistic terms	IVIFNs
Equally important (EI)	([1.0, 1.0], [0.0, 0.0])
Weakly important (WI)	([0.5, 0.6], [0.3, 0.4])
Strongly important (SI)	([0.6, 0.7], [0.2, 0.3])
Very important (VI)	([0.7, 0.8], [0.1, 0.2])
Absolutely important (AI)	([0.8, 0.9], [0.1, 0.2])

Assume the six renewable energy technologies including wind energy (A1), solar energy (A2), direct combustion (A3), combined heat and power (CHP) (A4), gasification (A5), and hydroenergy (A6), among which A3-A5 belongs to biomass. Wind energy (A1) has been used for a long time to grind grain, sail ships, and pump water, which could be changed into mechanical, electrical, and heating energy through wind turbine [63]. Solar energy (A2) converts solar radiation into other types of energy, including heat and electricity. Solar photovoltaic conversion process is widely used for generating electricity from solar energy [3]. Biomass is one of the renewable energy originating from organic materials [3]. Currently, there are mainly three technologies for energy generation related to biomass-direct combustion (A3), CHP (A4), and gasification (A5). Hydropower (A6) is a kind of renewable energy resource from water body [63]. By constructing hydropower plants, hydropower can be transformed into electricity.

Most renewable energy technology selection criteria utilized currently consist of economical, technical, social, and environmental factors. The economical factor evaluates the economic feasibility, considering investment cost, operation and maintenance cost, and service life [45]. The technical factor explains technology from maturity, efficiency, and reliability perspective [64]. Technology maturity presents the existing applications and improvement capability of the technology. Efficiency is assessed by the efficiency coefficient. Technology reliability could reflect the probability of operation with no failures happening. Social factors are associated with human being, including job creation [64] and social impact [65]. Job creation reflects that the adopted technologies create employment opportunity. Social impact

Table 6: The pair-wise comparison for the best criterion over the other criteria.

DMs	Best criterion	Other criteria CR1	CR2	CR3	CR4	CR5
DM1	CR2	([0.5, 0.6], [0.3, 0.4])	([1.0, 1.0], [0.0, 0.0])	([0.5, 0.6], [0.3, 0.4])	([0.6, 0.7], [0.2, 0.3])	([0.6, 0.7], [0.2, 0.3])
DM2	CR3	([0.5, 0.6], [0.3, 0.4])	([0.6, 0.7], [0.2, 0.3])	([1.0, 1.0], [0.0, 0.0])	([0.6, 0.7], [0.2, 0.3])	([0.7, 0.8], [0.1, 0.2])
DM3	CR1	([1.0, 1.0], [0.0, 0.0])	([0.5, 0.6], [0.3, 0.4])	([0.6, 0.7], [0.2, 0.3])	([0.7, 0.8], [0.1, 0.2])	([0.7, 0.8], [0.1, 0.2])

Table 7: The pair-wise comparison for other criteria over the worst criterion.

DMs	Worst criterion	Other criteria CR1	CR2	CR3	CR4	CR5
DM1	CR4	([0.7, 0.8], [0.1, 0.2])	([0.8, 0.9], [0.1, 0.2])	([0.5, 0.6], [0.3, 0.4])	([1.0, 1.0], [0.0, 0.0])	([0.6, 0.7], [0.2, 0.3])
DM2	CR5	([0.7, 0.8], [0.1, 0.2])	([0.7, 0.8], [0.1, 0.2])	([0.8, 0.9], [0.1, 0.2])	([0.6, 0.7], [0.2, 0.3])	([1.0, 1.0], [0.0, 0.0])
DM3	CR5	([0.8, 0.9], [0.1, 0.2])	([0.6, 0.7], [0.2, 0.3])	([0.7, 0.8], [0.1, 0.2])	([0.6, 0.7], [0.2, 0.3])	([1.0, 1.0], [0.0, 0.0])

could identify and quantify the human risk and consequence of certain technology. Environmental factor refers to potential environmental impact of renewable energy technology, which mainly includes land use and CO_2 emissions. Land use refers to a certain range of landscapes required to meet the requirement of the project [64]. CO_2 emissions reflect the emission reduction to the atmosphere by renewable energy technology [66]. The abovementioned criteria could be classified into benefit criterion (the higher the better) and cost criterion (the higher the poorer). The parameters of criteria for different renewable energy technologies and the criterion type are presented in Table 3.

This study selected 5 indicators to reflect EP performance, including the percentage of the population having access to clean fuels and technologies for cooking to the total population (CR1); percentage of the population having access to electricity to the total population (CR2); percentage of rural population with access to electricity to total rural population (CR3); percentage of urban population with access to electricity to total urban population (CR4); and log of the electric power consumption per capita (CR5). These indicators have already been utilized in previous research [25, 31], which reflect an increase of these variables showing a decrease in EP.

4.2. Implementation. Based on the abovementioned case study, this section empirically demonstrates the proposed IVIF BWM-QFD-VIKOR approach to select the most suitable renewable energy technology to reduce EP, including 3 stages.

Stage 1. Calculate the relative importance of energy poverty reduction requirements (CRs).

To calculate the weight of each criterion, three groups of DMs were invited to conduct focus group meeting, respectively, by applying the IVIF-BWM. Two groups of DMs, including DM1 and DM2, come from university and government, respectively. The rest of the group is from the consultancy company. The weights of the decision-making group are $\lambda = (0.333, 0.333, 0.333)^T$.

Table 8: Weights of evaluation criteria.

Evaluation criteria	Weights
CR1	0.367447823
CR2	0.299165523
CR3	0.224190784
CR4	0.050321881
CR5	0.058873989

Step 1. Select the best and worst criteria. The best and worst criteria have been decided by each decision-making group as shown in Table 4.

Step 2. Compare the best criterion with the other criteria based on Table 5. The comparison result has been listed in Table 6.

Step 3. Compare the other criteria with the worst criterion based on Table 5. The comparison result has been presented in Table 7.

Step 4. Obtain the optimal criteria weights of each DM.

The optimal criteria weights of each decision-making group are obtained through Equation (13). The model is solved with the help of Lingo 17.0. For instance, the model of DM1 is presented in the following formula:

$$\min \varepsilon,$$

$$s.t.,$$

$$\left|\mu_2^{L(1)} + \nu_j^{L(1)} - \mu_2^{L(1)} \cdot \nu_j^{L(1)} - 0.5\right| \le \varepsilon,$$

$$\left|\mu_2^{U(1)} + \nu_j^{U(1)} - \mu_2^{U(1)} \cdot \nu_j^{U(1)} - 0.6\right| \le \varepsilon,$$

$$\left|\nu_2^{L(1)} + \mu_j^{L(1)} - 0.3\right| \le \varepsilon,$$

$$\left|\nu_2^{U(1)} + \mu_j^{U(1)} - 0.4\right| \le \varepsilon, j = 1.3,$$

$$\left|\mu_2^{L(1)} + \nu_5^{L(1)} - \mu_2^{L(1)} \cdot \nu_5^{L(1)} - 0.6\right| \le \varepsilon,$$

$$\begin{gathered}
\left|\mu_2^{U(1)}+\nu_5^{U(1)}-\mu_2^{U(1)}\cdot\nu_5^{U(1)}-0.7\right|\le\varepsilon,\\
\left|\nu_2^{L(1)}+\mu_5^{L(1)}-0.2\right|\le\varepsilon,\\
\left|\nu_2^{U(1)}+\mu_5^{U(1)}-0.3\right|\le\varepsilon,\\
\left|\mu_1^{L(1)}+\nu_4^{L(1)}-\mu_1^{L(1)}\cdot\nu_4^{L(1)}-0.7\right|\le\varepsilon,\\
\left|\mu_1^{U(1)}+\nu_4^{U(1)}-\mu_1^{U(1)}\cdot\nu_4^{U(1)}-0.8\right|\le\varepsilon,\\
\left|\nu_1^{L(1)}+\mu_4^{L(1)}-0.1\right|\le\varepsilon,\\
\left|\nu_1^{U(1)}+\mu_4^{U(1)}-0.2\right|\le\varepsilon,\\
\left|\mu_2^{L(1)}+\nu_4^{L(1)}-\mu_2^{L(1)}\cdot\nu_4^{L(1)}-0.8\right|\le\varepsilon,\\
\left|\mu_2^{U(1)}+\nu_4^{U(1)}-\mu_2^{U(1)}\cdot\nu_4^{U(1)}-0.9\right|\le\varepsilon,\\
\left|\nu_2^{L(1)}+\mu_4^{L(1)}-0.1\right|\le\varepsilon,\\
\left|\nu_2^{U(1)}+\mu_4^{U(1)}-0.2\right|\le\varepsilon,\\
\left|\mu_3^{L(1)}+\nu_4^{L(1)}-\mu_3^{L(1)}\cdot\nu_4^{L(1)}-0.5\right|\le\varepsilon,\\
\left|\mu_3^{U(1)}+\nu_4^{U(1)}-\mu_3^{U(1)}\cdot\nu_4^{U(1)}-0.6\right|\le\varepsilon,\\
\left|\nu_3^{L(1)}+\mu_4^{L(1)}-0.3\right|\le\varepsilon,\\
\left|\nu_3^{U(1)}+\mu_4^{U(1)}-0.4\right|\le\varepsilon,\\
\left|\mu_5^{L(1)}+\nu_4^{L(1)}-\mu_5^{L(1)}\cdot\nu_4^{L(1)}-0.6\right|\le\varepsilon,\\
\left|\mu_5^{U(1)}+\nu_4^{U(1)}-\mu_5^{U(1)}\cdot\nu_4^{U(1)}-0.7\right|\le\varepsilon,\\
\left|\nu_5^{L(1)}+\mu_4^{L(1)}-0.2\right|\le\varepsilon,\\
\left|\nu_5^{U(1)}+\mu_4^{U(1)}-0.3\right|\le\varepsilon,\\
0<\mu_j^{L(1)}+\mu_j^{U(1)}-\nu_j^{L(1)}-\nu_j^{U(1)}<2,\\
\mu_j^{L(1)}<\mu_j^{U(1)},\nu_j^{L(1)}<\nu_j^{U(1)},\mu_j^{U(1)}+\nu_j^{U(1)}\le 1,\\
\sum_{j=1}^{5}\left(\mu_j^{L(1)}+\mu_j^{U(1)}-\nu_j^{L(1)}-\nu_j^{U(1)}\right)=2,\ \text{for all}\ C_j.
\end{gathered}\tag{33}$$

The solution of the abovementioned model, which is the optimal criteria weight of DM_1:

$$\begin{aligned}
\tilde{\omega}_1^{(1)}&=([0.3940,0.4940],[0.0774,0.0774])^{(1)},\\
\tilde{\omega}_2^{(1)}&=([0.5226,0.6303],[0.0774,0.0774])^{(1)},\\
\tilde{\omega}_3^{(1)}&=([0.2402,0.3146],[0.2774,0.2774])^{(1)},\\
\tilde{\omega}_4^{(1)}&=([0.1940,0.2940],[0.2221,0.2660])^{(1)},\\
\tilde{\omega}_5^{(1)}&=([0.2655,0.3578],[0.1774,0.1774])^{(1)}.
\end{aligned}\tag{34}$$

Step 5. Obtain the aggregated optimal weights for all DMs.

The DM weight in IIFWA operator is defined as $\lambda=(0.333,0.333,0.333)^T$. The aggregated optimal weights for all DMs are obtained by using Equation (14) in the following formula:

$$\begin{aligned}
\tilde{\omega}_1&=([0.4246,0.5050],[0.9225,0.8953]),\\
\tilde{\omega}_2&=([0.3897,0.4686],[0.8889,0.8627]),\\
\tilde{\omega}_3&=([0.3776,0.4493],[0.8194,0.7953]),\\
\tilde{\omega}_4&=([0.2286,0.2910],[0.8074,0.7657]),\\
\tilde{\omega}_5&=([0.2360,0.3279],[0.8029,0.7399]).
\end{aligned}\tag{35}$$

The crisp weight number of each criterion is obtained through Equation (15) in Table 8.

Stage 2. Calculating the weight of renewable energy technology selection (TR) criteria within IVIF-QFD.

Step 1. Develop the IVIF relationships matrix between CRs and TRs on QFD.

The correlation efficiency between CRs and TRs is obtained by asking the decision-making group to evaluate the impact of each TR on each CR through IVIF judgment, which are presented in Table A1 and corresponding IVIF linguistic terms are in Table A2 within supplementary material. The relationship matrix is presented in Table 9 after using Equation (14) to integrate the opinions from 3 decision-making groups.

Step 2. Obtain the IVIF weights of TRs.

The IVIF weights of TRs are obtained through Equation (15). The IVIF weight of TR11 can be calculated as follows.

$$\begin{aligned}
\mathrm{TW}_1&=w_1*\tilde{R}_{11}+w_2*\tilde{R}_{21}+w_3*\tilde{R}_{31}+w_4*\tilde{R}_{41}+w_5*\tilde{R}_{51}\\
&=0.3674*([0.5176,0.7282],[0,0.2718])\\
&\quad+0.2992*([0.6362,0.8410],[0,0.1590])\\
&\quad+0.2242*([0.6694,0.8737],[0,0.1590])\\
&\quad+0.0503*([0.5617,0.7842],[0,0.2158])\\
&\quad+0.0589*([0.2630,0.4755],[0.2470,0.5245])\\
&=([0.5457,0.5885],[0,4.5093E08]).
\end{aligned}\tag{36}$$

Defuzzify the IVIF weights of TRs. The defuzzification of the IVIF weights of TRs is calculated as in Equation (6).

Table 9: Relationship matrix between CRs and TRs.

	TR11	TR12	TR13	TR21	TR22	TR23	TR31	TR32	TR41	TR42
CR1	([0.5176, 0.7282], [0, 0.2718])	([0.2884, 0.4983], [0.2293, 0.5017])	([0, 0.1998], [0.5003, 0.8002])	([0.5234, 0.7586], [0, 0.2414])	([0.0345, 0.2346], [0.4645, 0.7654])	([0.2386, 0.4403], [0.2523, 0.5597])	([0.1756, 0.3783], [0.3111, 0.6217])	([0.3997, 0.652], [0, 0.3480])	([0, 0.1998], [0.5003, 0.8002])	([0.6362, 0.8410], [0, 0.1590])
CR2	([0.6362, 0.841], [0, 0.159])	([0.2386, 0.4403], [0.2523, 0.5597])	([0.0716, 0.2729], [0.4221, 0.7271])	([0.5996, 0.5234], [0, 0])	([0.0716, 0.2729], [0.4221, 0.7271])	([0.5688, 0.7707], [0, 0.2293])	([0.4149, 0.6362], [0, 0.3638])	([0.4149, 1], [0, 0])	([0.0716, 0.2729], [0.4221, 0.7271])	([0, 0.1998], [0.5003, 0.8002])
CR3	([0.6694, 0.8737], [0, 0.1262])	([0.3393, 0.5617], [0, 0.4383])	([0.1381, 0.3393], [0.3561, 0.6607])	([0.5234, 0.7586], [0, 0.2414])	([0.1036, 0.3045], [0.3919, 0.6955])	([0.6694, 0.8737], [0, 0.1263])	([0.3783, 0.5996], [0, 0.4004])	([0.3303, 0.5996], [0, 0.4004])	([0.0716, 0.2729], [0.4221, 0.7272])	([0, 0.1998], [0.5003, 0.8003])
CR4	([0.5617, 0.7842], [0, 0.2157])	([0.1678, 0.3681], [0.3306, 0.6319])	([0.0716, 0.2729], [0.4221, 0.7271])	([0.4755, 0.6960], [0, 0.3040])	([0.0678, 0.2679], [0.4313, 0.7321])	([0.5617, 0.7842], [0, 0.2158])	([0.4149, 0.6362], [0, 0.3638])	([0.2630, 0.4957], [0, 0.5043])	([0.0716, 0.2729], [0.4221, 0.7273])	([0, 0.1998], [0.5003, 0.8004])
CR5	([0.2630, 0.4755], [0.2470, 0.5245])	([0.0345, 0.2346], [0.4645, 0.7654])	([0, 0.1998], [0.5003, 0.8002])	([0.3158, 0.5234], [0.2083, 0.4766])	([0.0345, 0.2346], [0.4645, 0.7654])	([0.5836, 0.7997], [0, 0.2003])	([0.4683, 0.7112], [0, 0.2888])	([0.0678, 0.2679], [0.4313, 0.7321])	([0, 0.1998], [0.5003, 0.8002])	([0.6362,0.8410], [0, 0.1590])

Table 10: Correlation-based weights of TRs.

TR11	TR12	TR13	TR21	TR22	TR23	TR31	TR32	TR41	TR42
0.1623	0.0945	0.0414	0.1480	0.0432	0.1384	0.1070	0.1305	0.0375	0.0971

Table 11: The positive ($\tilde{f}_i^*$) and negative ($\tilde{f}_i^-$) ideal solutions regarding IVIF.

	The positive ideal solution $\left(\tilde{f}_i^*\right)$						Negative ideal solution $\left(\tilde{f}_i^-\right)$					
	$\tilde{\mu}_{\tilde{A}}\ (x)$ $[\mu_{\tilde{A}}{}^L, \mu_{\tilde{A}}{}^U]$		$\tilde{\nu}_{\tilde{A}}\ (x)$ $[\nu_{\tilde{A}}{}^L, \nu_{\tilde{A}}{}^U]$		$\tilde{\pi}_{\tilde{A}}\ (x)$ $[\pi_{\tilde{A}}\ L, \pi_{\tilde{A}}\ U]$		$\tilde{\mu}_{\tilde{A}}\ (x)$ $[\mu_{\tilde{A}}{}^L, \mu_{\tilde{A}}{}^U]$		$\tilde{\nu}_{\tilde{A}}\ (x)$ $[\nu_{\tilde{A}}{}^L, \nu_{\tilde{A}}{}^U]$		$\tilde{\pi}\ \tilde{A}(x)$ $[\pi_{\tilde{A}}{}^L, \pi_{\tilde{A}}{}^U]$	
Technical maturity	0.8	1	0	0	0	0.2	0.4	0.6	0.2	0.4	0	0.4
Reliability	0.8	1	0	0	0	0.2	0	0.2	0.5	0.8	0	0.5
Social impact	0.4	0.6	0.2	0.4	0	0.4	0	0.2	0.5	0.8	0	0.5

The example of the weight of TR11 is computed as follows:

$$(\text{Crisp value})\text{TW}_1 = \frac{0.5457 + 0.5885 - 0 - 4.5093\text{E}08}{2} = 0.5671. \tag{37}$$

Calculate the normalized IVIF weights of TRs. For example, the normalized weight of TR11 is obtained through Equation (17), shown in the following equation:

$$N(\text{TW}_1) = \frac{S(\text{TW}_1)}{\sum_{i=1}^{5} S(\text{TW}_i)} = 0.1623. \tag{38}$$

The correlation-based weights of TRs are presented in Table 10. The weights in Table 10 will be treated as input of the IVIF-VIKOR method.

Stage 3. Determine the ranking of alternatives through IVIF-VIKOR.

Step 1. Construct assessment matrix for alternatives.

The selected alternatives are evaluated based on literature review, which is shown in Table 3.

Step 2. Transform the linguistic term into IVIF value.

In the assessment matrix, the qualitative evaluation can be converted into IVIFN through linguistic scales in Table 1, and the evaluation of alternatives is given in Table A3 within supplementary material.

Step 3. Calculate the positive and negative ideal solutions.

The positive ideal solution (PIS) ($\tilde{f}_i^*$) and negative ideal solution (NIS) ($\tilde{f}_i^-$) for IVIFNs are obtained through Equations (19) and (20), whose corresponding solutions are given in Table 11. The positive (f^*) and negative (f^-) ideal solutions for interval numbers are calculated by Equations (21) and (22) , shown in Table 12.

Table 12: PIS and NIS for interval numbers.

	Initial investment (USD/kW)	Annual operation and maintenance cost (USD/kW-year)	Service life	Efficiency/capacity factor (%)	Job creation (jobs/MW)	Land requirement (m^2/GWh)	Emission (kg CO_2-eq/MWh)
PIS	1200	14	35	85	22.9	126	2
NIS	6820	83	20	12	7.8	25000	160

Table 13: S and R interval numbers.

	$[S_k{}^L, S\,k^U]$	$[R_k^L, R_k^U]$
Wind energy	[0.4537, 0.5125]	[0.1384, 0.1383]
Solar energy	[0.4964, 0.7667]	[0.1480, 0.1617]
Direct combustion	[0.3612, 0.4972]	[0.1305, 0.1305]
CHP	[0.5191, 0.7284]	[0.1480, 0.1623]
Gasification	[0.4849, 0.6712]	[0.1480, 0.1480]
Hydropower	[0.1005, 0.3307]	[0.0609, 0.0852]

Table 14: Q interval numbers.

	$[Q_k^L, Q_k^U]$
Wind energy	[0.6475, 0.6917]
Solar energy	[0.7268, 0.9972]
Direct combustion	[0.5390, 0.6411]
CHP	[0.7438, 0.9712]
Gasification	[0.7182, 0.8580]
Hydropower	[0, 0.2925]

Step 4. Calculate the group utility and individual regret values.

Group utility and individual regret values for IVIFNs are $S(A_k)$ in Equation (23) and $R(A_k)$in Equation (24), for interval value are $[S_k^L, S_k^U]$ in Equations (26) and (27), and $[R_k^L, R_k^U]$ in Equations (28) and (29), respectively. The result is presented in Table 13.

Step 5. Obtain interval $Q_k = [Q_k^L, Q_k^U]\,; k = 1, 2, \cdots, p$, by Equations (30) and (31). The results are shown in Table 14. $S^* = 0.1005$, $S^- = 0.7667$, $R^* = 0.0609$, and $R^- = 0.1623$

Step 6. Rank the alternatives. Using ranking rules in Table 2 and step 5, the result is shown as follows: A6 > A3 > A1 > A4 > A2 > A5.

5. Discussions

This paper proposes a novel renewable energy technology selection model for EP alleviation by integrating BWM-QFD-VIKOR methods with IVIFNs as a new scientific evaluation method. The proposed model is a rational and practical approach to improving the efficiency of renewable energy selection. At first, the importance degree of each CR and the correlation between CR and TR have been assessed in IVIFNs instead of traditional crisp numbers, which ensures a more accurate assessment from DMs. Next, the IVIF-BWM method calculates the importance degree of CRs by considering the relationships among criteria and the uncertainty and vagueness of decision-making process. Finally, the proposed IVIF-QFD approach transforms the customer demands into technology features to ensure that all selected technical criteria are in accord with customer expectations. Thereby, the selected renewable energy technology could better satisfy the demand for EP reduction requirements.

5.1. Managerial Implication. This paper can be introduced to the policy-maker for selecting appropriate renewable energy technology to alleviate EP by considering the ranking result. According to the result of IVIF-QFD, we obtain that the most significant CRs for EP alleviation is access to clean fuels and technologies for cooking (CR1), and the most important technology requirement is the initial investment (TR1). The correlations among CRs are examined by IVIF-BWM, which could assist to calculate the related relationships more accurately [70]. The result of the IVIF BWM-QFD-VIKOR approach presents that the most rational renewable energy technology is hydropower (A6) to reduce EP. The ranking of other alternatives is direct combustion (A3), wind energy (A1), CHP (A4), solar energy (A2), and gasification (A6), respectively. The result reflects that DMs could adopt the proposed model to take appropriate measures for EP alleviation.

6. Conclusions

This study proposed an integrated BWM-QFD-VIKOR model under IVIFNs to select suitable renewable energy technology for EP alleviation. In terms of MCDM techniques, an integrated BWM-QFD-VIKOR technique is a new method, having limited researches adopt them individually. It is the first time to combine all the methods, which represents one of the scientific contributions of this study. Current research always uses the crisp number to deal with the weight of CR and the relationship between CR and TR. Information missing is likely to occur because the vagueness of subjective evaluation could not be fully reflected by crisp numbers. IVIF number has been used in this study to present the vagueness and uncertainties of DMs while making evaluation. IVIF-BWM has been proposed in this study to calculate the weight of CRs by considering not only the interaction among criteria but also showing the vagueness of decision-making process. After that, the IVIF-QFD could accurately understand the relationship between EP reduction expectations and renewable energy technology requirements, which enables the selected technical features to satisfy the EP alleviation requirements. Finally, based on the importance degree of different technical features, the IVIF-VIKOR could prioritize renewable energy technologies by considering the mutual concession among alternatives. According to the result of the case study, the most significant feature of CR is access to clean fuels and technologies for cooking (CR1). The most important features for TRs are initial investment (TR1) and capacity factor (TR5), respectively. With the effectiveness of the proposed model, it has been confirmed that hydropower is the most important renewable energy resource for reducing EP.

Limitations still exist in this study. The data of this paper is collected from previous studies, and future work can do some dynamic evaluations in several consecutive years to explore the ranking difference among renewable energy technology. It would also be interesting to adopt other methods to investigate the influencing mechanism of renewable energy technology on EP.

Abbreviations

BWM:	Best-worst method
CFPS:	China family panel studies
CHP:	Combined heat and power
CRs:	Customer requirements
DM:	Decision maker
DMs:	Decision makers
EP:	Energy poverty
FAHP:	Fuzzy analytic hierarchy process
HoQ:	House of quality
IFS:	Intuitionistic fuzzy set
IIFWA:	Interval-valued intuitionistic fuzzy weighted averaging
IVIF:	Interval-valued intuitionistic fuzzy
IVIFN:	Interval-valued intuitionistic fuzzy number
IVIFNs:	Interval-valued intuitionistic fuzzy numbers
IVIFS:	Interval-valued intuitionistic fuzzy set
MCDM:	Multicriteria decision-making
NIS:	Negative ideal solution
PIS:	Positive ideal solution
PV:	Photovoltaic
QFD:	Quality function deployment
RE:	Renewable energy
TOPSIS:	Technique for ordering preference by similarity to ideal solution
TRs:	Technical requirements.

Data Availability

Data are available in supplementary information files.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The work described in this paper was supported by the grant from the Research Committee of the Hong Kong Polytechnic University under student account code RK3E and the grant "Postdoctoral Fellowships Scheme" from the Research Committee of the Hong Kong Polytechnic University under project ID-P0031541 (account: G-YW4Y).

Supplementary Materials

The supplementary material contains the relationship matrix obtained from 3 decision makers (Table A1), corresponding relationship matrix based on interval-valued intuitionistic fuzzy number (Table A2), and decision matrix of the renewable technology selection for energy poverty reduction (Table A3). *(Supplementary Materials)*

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