



Article A Combined Fuzzy Optimization Model for the Location of an Intelligent Energy-Efficient Manufacturing Industrial Park

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Abstract: With the background of implementing carbon peaking and carbon neutralization, identifying methods to realize energy-saving and carbon reduction effectively has become an important issue in the intelligent energy-conservation manufacturing industry. During the process of achieving this goal, determining an optimal location for a low-carbon and intelligent manufacturing industrial park is a foremost decision-making problem for manufacturing corporations' energy-efficient development. The article established a multi-criteria decision framework to assist manufacturing companies when selecting suitable industrial park sites. To begin with, an evaluation criteria framework is confirmed by literature search. Then, a fuzzy optimization model, which combines the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) is presented, where fuzzy TOPSIS is used to determine the decision-maker criteria weights. Then, criteria weights are calculated by the optimization model with construction of a Lagrange function. Moreover, the fuzzy VIKOR method is applied to sort alternatives and choose the best alternative location. In addition, five alternative sites for a manufacturing company are evaluated and ranked according to the values of the ranking index as a numerical case to demonstrate the proposed framework's application. Finally, a comprehensive analysis of diverse methods and sensitivity analyses for the volatility in criteria weights and decision-maker weights is illustrated to confirm that the framework is practicable for the problem of intelligent and sustainable manufacturing industrial park-site selection.

Keywords: manufacturing industrial park-site selection; optimization model; interval intuitionistic fuzzy sets; fuzzy TOPSIS; fuzzy VIKOR

1. Introduction

Site selection is an important issue for many types of businesses, including services, retail industries and manufacturing industries [1]. With the gradual end of traditional manufacturing and under the background of the "double carbon" era, the energy-efficient production of intelligent manufacturing has become the main melody of the contemporary manufacturing industry [2,3]. As an emerging production model based on the traditional manufacturing industry, energy-saving intelligent manufacturing is not only considered to be promising but also has become very popular in recent years, and it is universally acknowledged that manufacturing is an indispensable part of the national economy [4]; thus, the selection of intelligent manufacturing industry sites has become a vital and strategic decision-making issue, which involves the planning of multitudinous resources for the sustainable development of companies.

The survival and development of the manufacturing industry is a matter of concern to entrepreneurs, consumers and government [5]. Manufacturing companies have products



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). produced and sell them for profits, which leads to product improvement, technological innovation and a new round of manufacturing. Consumers need to obtain the goods produced by the manufacturer and meet their daily needs, and the government has to pay close attention to the development of the manufacturing industry, obtaining market information, and thus macro-control the entire economy. Therefore, the development of the manufacturing sector is crucial to a country's economic growth.

A low-carbon intelligent manufacturing industrial park refers to the comprehensive and systematic integration of the two-carbon concept in the planning, management and operation process of the park, precise planning of the goal setting and implementation path of carbon neutrality, and relying on digital means to achieve the goal of energy saving and carbon reduction. Intelligent management is used to promote the low-carbon transformation of the industry and the recycling of resources to achieve the balance of carbon emissions in the low-carbon intelligent manufacturing industrial park. The key to the success of the intelligent manufacturing industrial park is site selection [6]. According to a survey, the impact of site selection on the success or failure of the manufacturing industrial park is at least 70%. The site has a direct impact on the industry's competitiveness, and the specific site determines the length of the effective distance that the industrial park provides for potential customers in the region. It also determines the level of the manufacturing industrial park revenue, reflecting the value of the site as a resource [7,8].

Selecting a correct site has many positive effects, such as increasing market share and enhancing the ability to attract consumers and increasing revenue. Failure in site selection will result in low investment efficiency, low economic efficiency, and a waste of social resources; these adverse effects are irreversible [9]. As manufacturing industrial parks generally have large investment scales and long investment periods, the location decision is the top priority before any other decisions—the subsequent defects such as in the service strategy, marketing behavior, product type, commodity pricing, etc., can be easily compensated and changed. However, it is difficult to modify the manufacturing industry site when it is determined, and if the process of site selection fails, it is difficult to erase the negative impact of a bad site decision and it will cause significant losses [10]. Due to improper site selection, some manufacturing industries are closed for business, or forced to adjust their business models and carry out structural transformation and asset restructuring to make up for the deficiency brought by site problems [11]. Therefore, whether problems arise from manpower, material resources or the long-term development of a company, performing adequate prerequisite research and preparations for a manufacturing industrial park site is an important decision-making issue with strategic implications.

Site selection mainly refers to the process of investigating, analyzing, comparing, and selecting several sites, and ultimately determining the right to use land or property to prepare for the construction of a business site according to a company's development strategy [12,13]. The processes mentioned above require a synthetic analysis of marketing, geography, operating cost, and so forth, and then a few prospective alternative sites are analyzed on the basis of a variety of criteria. In consequence, location selection can be defined as a multi-criteria decision-making problem [14]. First of all, the selection criteria need to be determined. Second, a variety of multi-criteria decision methods are generally used in location problems to choose the optimal site, such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [15,16], VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [17,18], and the preference ranking organization method for enrichment evaluations (PROMETHEE) [19,20]. Site-selection issues are widely occurring in everyday life, and it is a universally applicable method to firstly determine multiple criteria and then use the multi-criteria decision-making (MCDM) method to select the optimum site. In this paper, based on this idea, a TOPSIS and Lagrange function-based model is used for the multi-criteria manufacturing industrial park-selection problem, the criteria system is determined by literature search, and the fuzzy VIKOR method is presented to rank and select the optimal site from several alternative sites.

Within this paper, a comprehensive assessment framework is established so as to study the site-selection problems of intelligent manufacturing industrial parks. The framework can assist companies in seizing market share, establishing location accurately, and standing out in fierce market competition. Currently, research on the location of manufacturing industrial parks under the background of energy-efficient and intelligent manufacturing is rare, and the information involved in the assessment process usually has the properties of being uncertain and fuzzy. In addition, given the advantages of the MCDM techniques, models based on multiple methods can produce more robust solutions than models based on a single method [21,22]. Therefore, this paper presents a scientific MCDM framework that combines fuzzy TOPSIS and fuzzy VIKOR to address the problem of manufacturing industrial park-site selection under ambiguity.

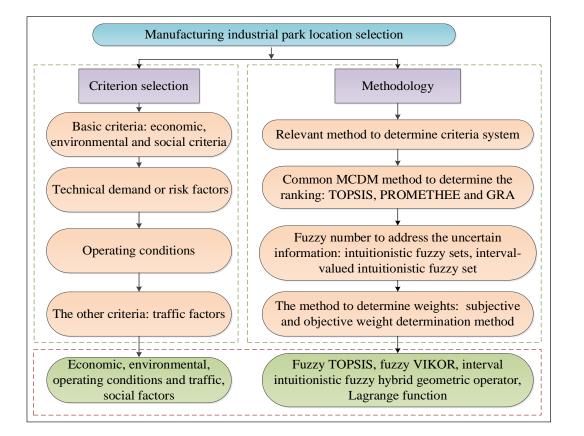
The main contributions of the established model include considering multiple types of conflicting criteria, including quantitative and qualitative criteria, and then based on the usage of fuzzy multiple attribute decision-making framework, an optimum site from several alternative sites is selected [5]. The overall ideas of the paper are as follows: Firstly, establishing a site-selection criteria system through a literature search. The criteria system comprehensively analyzes the criteria that affect decision-making from the perspectives of economic characteristics, environmental conditions, social factors, operating conditions and traffic factors under the premise of sustainable development. Then, the MCDM model—on the basis of fuzzy TOPSIS and fuzzy VIKOR—is used to choose the optimal site from the determined alternatives. TOPSIS and VIKOR are widely used methods to address MCDM problems, which have the following advantages. TOPSIS is a comprehensive evaluation method based on the distance between good and bad solutions, it can make full use of original data information, and its results can fully reflect the closeness of each evaluation scheme to the optimal scheme. In addition, it has no strict limit on the sample size, and the data calculation process without the data test is simple and convenient. The characteristics of the VIKOR method are that it can obtain the compromised solution closest to the ideal solution and maximize group benefit and minimize individual loss. A solution obtained by this method is easier to be accepted by decision-makers. Considering the advantages of above methods, the weights of decision-makers (DMs) in the decision-making procedure are derived through the modified TOPSIS method. An optimizing model based on the Lagrange function is set up for the calculation of attribute weights.

For the purpose of solving the uncertainty in the process of human cognition and describing the fuzziness of the decision-making environment, the IIFOWGw operator is applied to process the uncertainty of data information. Within this paper, interval intuitionistic fuzzy numbers are used to characterize data—interval-valued intuitionistic fuzzy sets have the dual nature of characterizing the high uncertainty of a system and the hesitancy degree of the decision-maker when considering the MCDM problem, and they can describe the strong fuzziness of decision-making problems more effectively. Aiming to achieve the sustainable development of the manufacturing industry, energy-saving and intelligent manufacturing industrial parks have been given considerable attention since the rise of energy conservation and emission reduction [23]. Therefore, a numerical example has an important reference value for implementation in other manufacturing industries.

The remainder of this paper is arranged as follows. The literature review is displayed in Section 2. The related knowledge and MCDM framework combining fuzzy TOPSIS and fuzzy VIKOR are presented in Sections 3 and 4. In Section 5, validity and practicability are illustrated with a numerical example about the site selection of a sustainable and intelligent manufacturing industrial park. Then, comparison and sensitivity analysis are presented to verify the framework's robustness and feasibility in Section 6. Finally, conclusions and prospects about this study are displayed in Section 7.

2. Literature Review

Site selection is relevant to the success or failure of an entire business operation model and a manufacturing company's sustainability development. The literature connected with



this paper is primarily from two separate categories: criteria selection and methodology. The analysis of current papers is demonstrated in Figure 1.

Figure 1. The analysis process of existing research.

2.1. Criteria Selection

Site selection cannot be simply considered as site determination, since the site-selection problem presents a complex structure, and both tangible and intangible factors can affect the cost and revenue of the company [24]. Therefore, DMs usually determine the criteria that influence the selection from all aspects, such as technology, economy, environment, society, site characteristics and cost, etc. Chou [25] implemented a site-selection framework for airline transshipment container port sites, which was based on multiple criteria such as the port site, hinterland economy, port physical attributes, port efficiency and cost. Chou et al. [26] considered objective criteria and subjective criteria simultaneously in facility site selection, and then selected the optimizing site under the group decision-making conditions. According to the criteria of cost, economic characteristics, environmental considerations, sustainability, transportation, etc., Zolfani et al. [27] studied the site-selection problem of shopping centers. Latinopoulos and Kechagia [28] presented an indicator system for technical, economic and environmental aspects to choose the right wind site. From the perspective of sustainable development, Rao et al. [6] proposed that the economy, the environment, and society can be used as criteria to select the logistics center of modern cities. Çebi and Otay [29] selected location indicators of cement factories such as resource availability, strategic factors, cost factors and so forth, and analyzed the relationship between alternatives and criteria to choose the optimal site. Wang et al. [30] selected the best site for a solar-power plant considering lots of factors such as social, technical, economic, environmental and site characteristics. Sennaroglu and Celebi [7] presented a method for selecting the site of military airfields, which involved factors including climate, geography, security, infrastructure, and so forth, to select the optimum site. As seen from the above papers, we can conclude that the location issue is generally based upon diverse types of

conflicting factors, involving characteristics of subjectiveness, objectiveness, quantification, and quantitation. The majority of studies choose the best site from the perspective of sustainability and green development [31]. Therefore, in this paper, we construct a criteria assessment system from five aspects based on sustainability development.

2.2. Methodology

For a multi-attribution decision problem, the MCDM framework should be identified to tackle the MCDM issue. MCDM methods involving TOPSIS and VIKOR are considered effective and practical for solving site-selection problems [32]. Fuzzy Grey Relation Analysis (GRA) provides the grey relation degree for the alternative rankings, and it is also regarded as an effective method for addressing the MCDM problem [33]. MCDM methods can select an optimal site among alternative sites based on multiple criteria. Many extant research studies have verified the feasibility of these methods [34,35].

Chou [12] established a novel MCDM model considering a hierarchical analysis structure for airlines to choose the optimum transshipment container port site with the aim of reducing the transportation cost of international trade containers. Vahidnia Mohammad H et al. [36] propose a hybrid decision-making framework based on the analytic hierarchy process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for selecting the optimal site for a new fire station in Imam Khomeini port. Rodriguez Vazquez S and Mokrova N [37] propose the development of a hybrid method of multi-criteria analysis using the hierarchical analysis technique and the Technique for Order of Preference by Similarity to Ideal Solution with a specific focus on the selection of sites for dams. Shao Meng et al. [38] proposed a three-stage decision framework based on Geographic Information System (GIS) and Multi-Criteria Decision-Making (MCDM) to determine potential marine areas, extract and evaluate site alternatives. Abhishek Guleria and Rakesh Kumar Bajaj [39] incorporate (R,S)-Norm Pythagorean fuzzy entropy and respective discriminant measure in the VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) techniques to deal with the hydrogen power plant site-selection problem. Tufail Faiza and Shabir Muhammad [40] propose a hybrid model for multi-criteria decision-making based on bipolar fuzzy soft β covering-based bipolar fuzzy rough sets using the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique, and the proposed technique is applied to determine the selection of a site for a renewable energy project (solar power plant). Chou et al. [13] put forward a new MCDM method to tackle the facility location issue; the system integrated the fuzzy set concept and several MCDM techniques to evaluate the alternatives. Kabir and Sumi [9] developed an MCDM model by combining an analytic hierarchy process (AHP) and the preference ranking organization method for enrichment evaluation (PROMETHEE) to study the location problems of substations under the influence of many conflicting factors. Latinopoulos and Kechagia implemented a comprehensive assessment of the MCDM framework, which focused on multiple decision analysis techniques for selecting the best locations for wind farm projects. Rao et al. [6] used a novel MCDM model for site selection, which introduced the linguistic 2-tuple, and the proposed methodology was used to rank and select the optimum sites for logistics centers in modern cities for sustainable development. Cebi and Otay [16] suggested a systemic MCDM method to tackle the cement plant equipment site problem. Gupta and Mehlawat [8] presented a new MCDM model to tackle the issue of plant location. Taking the energy structure based on thermal energy and hydropower of Vietnam as an example, Wang et al. [17] provided an MCDM model involving data envelopment analysis (DEA), fuzzy AHP and TOPSIS to choose the best location. Most of the literature focused on location issues according to preference ranking organization method for enrichment evaluation (PROMETHEE) and TOPSIS methods, while only a few studies researched site-selection issues based on the VIKOR method.

In the above papers, a critical issue in location is dealing with indefinite information in the assessment procedure. Normally, some metrics are quantitative while others are qualitative—quantitative values can be expressed by exact values, but qualitative values have a basis of language evaluation and cannot be quantified, so the fuzzy set theory is introduced to change this situation [41]. Kabir and Sumi [9] introduced intuitionistic fuzzy numbers (IFNs) to the MCDM method based on the AHP and PROMETHEE, which are effectively used for the pairwise comparison scale of the fuzzy AHP method. Rao et al. [6] established a decision-making model to evaluate potential logistics center sites and select the best one, where linguistic 2-tuples are applied to quantify the linguistic variables. The MCDM methods on the basis of fuzzy set theory have been extensively incorporated into such research studies to address the uncertain information for language evaluation values [42]. To more comprehensively summarize this vague, uncertain, and subjective information, intuitionistic interval valued fuzzy sets (IIVFSs) are used in this paper.

When MCDM methods are used for site selection, the next question is determining the criteria weights. According to the current research, the determination methods of subjective weight involve expert evaluation methods, AHP, BWM, and so forth [43–45]. Among this, as a new method that combines qualitative criterions and quantitative criterions, the best-worst method (BWM) compares with traditional methods such as AHP. It has advantages such as the number of comparison between indexes is significantly reduced, the consistency of the results is relatively high, and the calculation process is convenient. Based on the above advantages, best-worst method has been widely used in the last few years [46]. However, due to the DMs' personal experience, inconsistencies or errors often occur in the evaluation process. Therefore, the weight of subjective criteria should be computed by employing a method of quantification. The principal component method and entropy-weighing method are normally conducted on the basis of the real data, so the results acquired are more credible, but the wrong data also result in bias in the assessment results [47–49]. Thus, the weight of subjective criteria is obtained by constructing the Lagrange function in this paper.

3. Preliminaries

Within this section, we review the primary concepts of IVFSs as well as IIVFSs and the multiplication operation. The addition operation of IIVFSs and the conception of an interval intuitionistic fuzzy hybrid geometric operator are also briefly introduced in this part.

3.1. Basic Concepts of Intuitionistic Fuzzy Sets (IVFSs) and Interval Intuitionistic Fuzzy Sets

Definition 1. Suppose X is non-empty classical domain, if A is an IVFSs on X,

$$\widehat{A} = \left\{ \left\langle x, \mu_{\widetilde{A}}(x), v_{\widetilde{A}}(x) \right\rangle \, \middle| x \in X \right\} \tag{1}$$

 $\mu_{\widetilde{A}}(x)$ and $v_{\widetilde{A}}(x)$ were degree of membership and degree of non-membership for component x pair to \widetilde{A} , $\pi_{\widetilde{A}} = 1 - \mu_{\widetilde{A}}(x) - v_{\widetilde{A}}(x)$ represent degree of hesitancy of component x, specific numerical values range are stated as follows. $\mu_{\widetilde{A}}(x) \in [0,1]$; $v_{\widetilde{A}}(x) \in [0,1]$; $\pi_{\widetilde{A}}(x) \in [0,1]$; $0 \le \mu_{\widetilde{A}}(x) + v_{\widetilde{A}}(x) \le 1$.

Definition 2. Suppose X is non-empty classical domain. If \tilde{B} is an IIVFSs on X. Respectively, the upper and lower endpoints of interval-valued membership degree and interval-valued non-membership degree are denoted as: $\mu_{\tilde{B}L}(x)$; $\nu_{\tilde{B}L}(x)$; $\nu_{\tilde{B}L}(x)$; $\nu_{\tilde{B}L}(x)$.

$$\widetilde{B} = \left\{ \left\langle x, \left[\mu_{\widetilde{B}L}(x), \mu_{\widetilde{B}U}(x) \right], \left[v_{\widetilde{B}L}(x), v_{\widetilde{B}L}(x) \right] \right\rangle \, \middle| x \in X \right\}$$
(2)

 $[\mu_{\tilde{B}L}(x), \mu_{\tilde{B}U}(x)]$ denotes interval-valued membership degree, $[v_{\tilde{B}L}(x), v_{\tilde{B}U}(x)]$ denotes the interval-valued non-membership degree.

 $\pi_{\widetilde{B}} = 1 - \mu_{\widetilde{B}}(x) - v_{\widetilde{B}}(x) = \left[1 - \mu_{\widetilde{B}U}(x) - v_{\widetilde{B}U}(x), 1 - \mu_{\widetilde{B}L}(x) - v_{\widetilde{B}L}(x)\right] \text{ denotes interval-valued hesitancy degree.}$

In the above formula: $\mu_{\tilde{B}L}(x) \in [0,1]$; $\mu_{\tilde{B}U}(x) \in [0,1]$; $v_{\tilde{B}L}(x) \in [0,1]$; $v_{\tilde{B}U}(x) \in [0,1]$; $v_{\tilde{B}U}(x) \in [0,1]$ and $\mu_{\tilde{B}U}(x) + v_{\tilde{B}U}(x) \leq 1$.

Note: when $\mu_{\tilde{B}L}(x) = \mu_{\tilde{B}U}(x)$ and $v_{\tilde{B}L}(x) = v_{\tilde{B}U}(x)$, IIFSs \tilde{B} degenerate into IFSs \tilde{A} . Therefore, IIVFSs are a generalization of intuitionistic fuzzy sets.

Definition 3. Assume there are two interval intuitionistic fuzzy sets \tilde{B}_1 ; \tilde{B}_2 and the algorithm can be defined as follows:

$$\widetilde{B}_{1} \oplus \widetilde{B}_{2} = \left(\left[\mu_{\widetilde{B}_{1}L} + \mu_{\widetilde{B}_{2}L} - \mu_{\widetilde{B}_{1}L} \mu_{\widetilde{B}_{2}L'}, \mu_{\widetilde{B}_{1}U} + \mu_{\widetilde{B}_{2}U} - \mu_{\widetilde{B}_{1}U} \mu_{\widetilde{B}_{2}U} \right], \left[v_{\widetilde{B}_{1}L} v_{\widetilde{B}_{2}L'}, v_{\widetilde{B}_{1}U} v_{\widetilde{B}_{2}U} \right] \right)
\widetilde{B}_{1} \otimes \widetilde{B}_{2} = \left(\left[\mu_{\widetilde{B}_{1}L} \mu_{\widetilde{B}_{2}L'}, \mu_{\widetilde{B}_{1}U} \mu_{\widetilde{B}_{2}U} \right], \left[v_{\widetilde{B}_{1}L} + v_{\widetilde{B}_{2}L} - v_{\widetilde{B}_{1}L} v_{\widetilde{B}_{2}L'}, v_{\widetilde{B}_{1}U} + v_{\widetilde{B}_{2}U} - v_{\widetilde{B}_{1}U} v_{\widetilde{B}_{2}U} \right] \right)
\lambda \widetilde{B} = \left[1 - (1 - \mu_{\widetilde{B}L})^{\lambda}, 1 - (1 - \mu_{\widetilde{B}U})^{\lambda} \right], \left[v_{\widetilde{B}L}^{\lambda}, v_{\widetilde{B}U}^{\lambda} \right], \lambda > 0
\widetilde{B}^{\lambda} = \left(\left[\mu_{\widetilde{B}L}^{\lambda}, \mu_{\widetilde{B}U}^{\lambda} \right], \left[1 - (1 - v_{\widetilde{B}L})^{\lambda}, 1 - (1 - v_{\widetilde{B}U})^{\lambda} \right] \right), \lambda > 0$$
(3)

3.2. Interval Intuitionistic Fuzzy Hybrid Geometric Operator

Definition 4. Suppose $\widetilde{A_j} = \langle [\mu_{jL}, \mu_{jU}], [v_{jL}, v_{jU}] \rangle (j = 1, 2, 3 \cdots n)$ is a congregation composed of interval intuitionistic fuzzy numbers. IIFOWG is a mapping: $F_I^n \to F_I$; it can be represented as:

$$IIFOWG_{w}(\widetilde{A}_{1},\widetilde{A}_{2},\widetilde{A}_{3},\cdots,\widetilde{A}_{n}) = (\widetilde{A}_{\sigma(1)})^{\omega_{1}} \otimes (\widetilde{A}_{\sigma(2)})^{\omega_{2}} \otimes (\widetilde{A}_{\sigma(3)})^{\omega_{3}} \otimes \cdots \otimes (\widetilde{A}_{\sigma(n)})^{\omega_{n}}$$
(4)

The specific form of the interval intuitionistic fuzzy hybrid geometric operator can be represented as: IIFOWG_w($\widetilde{A}_1, \widetilde{A}_2, \widetilde{A}_3, \dots, \widetilde{A}_n$) = $\begin{bmatrix} \prod_{j=1}^n a_{\sigma(j)}^{\omega_j}, \prod_{j=1}^n b_{\sigma(j)}^{\omega_j} \end{bmatrix}$, $1 - \prod_{j=1}^n (1 - c_{\sigma(j)})^{\omega_j}$, $1 - \prod_{j=1}^n (1 - c_{\sigma(j)})^{\omega_j}$ weight vector of operator is $\omega = (\omega_1, \omega_2, \omega_3, \dots, \omega_n)^T$, $\omega_j \in [0, 1]$ ($j = 1, 2, 3 \dots n$), $\sum_{j=1}^n \omega_j = 1$.

4. MCDM Framework Based on Interval-Valued Intuitionistic Fuzzy Sets

Within this section, the MCDM model, which integrates fuzzy TOPSIS and fuzzy VIKOR, is established to select the optimization of the alternative locations. The detailed procedures of the proposed model are demonstrated in Figure 2.

4.1. Problem Description

For the issue of an MCDM problem, the alternative set $Y = \{Y_1, Y_2, Y_3 \cdots Y_m\}$, decision-maker set $K = \{K_1, K_2, K_3 \cdots K_n\}$ and attribute set $G = \{g_1, g_2, g_3 \cdots g_n\}$ of the multi-attribute group decision-making problem should be confirmed at first. The weight vector of attribute $G_j (j = 1, 2, \dots n)$ is determined as $\omega = (\omega_1, \omega_2, \cdots \omega_n)^T$, and the attribute weight or decision-maker weight information are completely unknown.

Suppose $\tilde{R}_k = (\tilde{r}_{ijk})_{n*m} = ([\mu_{ijk}^L, \mu_{ijk}^U], [v_{ijk}^L, v_{ijk}^U])_{n*m}$ is an interval intuitionistic fuzzy decision matrix provided by decision-maker d_k , and $\tilde{r}_{ijk} = (\tilde{\mu}_{ijk}, \tilde{v}_{ijk})$ is an attribute value provided by decision-maker d_k for alternative y_i with respect to attribute g_i . $\tilde{\mu}_{ijk}$ denotes the degree to which the alternative y_i satisfies the attribute g_i , and \tilde{v}_{ijk} denotes the degree to which the alternative y_i does not satisfy the attribute g_i . $\tilde{\mu}_{ijk}$ and \tilde{v}_{ijk} should be valued within a certain range, and demonstrated as: $\tilde{\mu}_{ijk} = [\mu_{ijk}^L, \mu_{ijk}^U], \tilde{v}_{ijk} = [v_{ijk}^L, v_{ijk}^U];$ $\tilde{\mu}_{ijk} \subset [0,1]; \tilde{v}_{ijk} \in [0,1]; \tilde{\mu}_{ijk} + \tilde{v}_{ijk} \leq 1$. The current conundrum is to determine a valid decision analysis method and rank the existing alternatives.

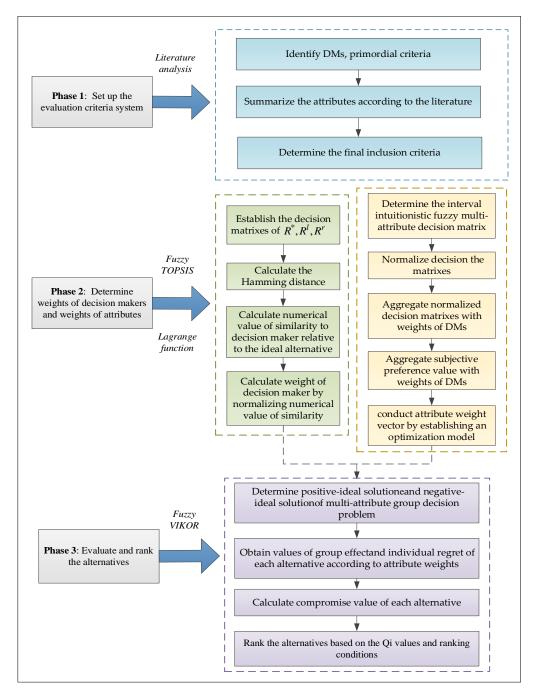


Figure 2. The detailed procedures of the MCDM framework.

4.2. Improved TOPSIS Method to Determine Decision-Maker Weight

Step 1: Establish positive-ideal decision matrix, $R^* = \left(\tilde{r}_{ij}^*\right)_{n \times n} = \left\langle \left(\mu_{ijL}^*, \mu_{ijU}^*\right), \left(v_{ijL}^*, v_{ijU}^*\right)\right\rangle_{n \times n}$, where $\mu_{ijL}^* = \frac{1}{q}\sum_{k=1}^q \mu_{ijL}^k$; $\mu_{ijU}^* = \frac{1}{q}\sum_{k=1}^q \mu_{ijU}^k$; $v_{ijL}^* = \frac{1}{q}\sum_{k=1}^q v_{ijL}^k$; $v_{ijU}^* = \frac{1}{q}\sum_{k=1}^q v_{ijU}^k$.

 R^* is the average matrix of the total decision-makers' interval intuitionistic fuzzy preference relation matrix, which reflects the group opinion to some extent.

Step 2: Define left-negative ideal decision matrix $R^l = (\tilde{r}_{ij}^l)_{n \times n} = \langle (\mu_{ijL}^l, \mu_{ijU}^l), (v_{ijL}^l v_{ijU}^l) \rangle_{n \times n}$ and right-negative ideal decision matrix $R^r = (\tilde{r}_{ij}^r)_{n \times n} = \langle (\mu_{ijL}^r, \mu_{ijU}^r), (v_{ijL}^r, v_{ijU}^r) \rangle_{n \times n}$, where:

$$\begin{split} \mu_{ijL}^{l} &= \min_{1 \le k \le q} \left\{ \mu_{ijL}^{k} \right\}; \mu_{ijU}^{l} = \min_{1 \le k \le q} \left\{ \mu_{ijU}^{k} \right\}; v_{ijL}^{l} = \max_{1 \le k \le q} \left\{ v_{ijL}^{k} \right\}; v_{ijU}^{l} = \max_{1 \le k \le q} \left\{ v_{ijU}^{k} \right\}; \\ \mu_{ijL}^{r} &= \max_{1 \le k \le q} \left\{ \mu_{ijL}^{k} \right\}; \mu_{ijU}^{r} = \max_{1 \le k \le q} \left\{ \mu_{ijU}^{k} \right\}; v_{ijL}^{r} = \min_{1 \le k \le q} \left\{ v_{ijL}^{k} \right\}; v_{ijU}^{r} = \min_{1 \le k \le q} \left\{ v_{ijU}^{k} \right\}; \end{split}$$

Step 3: Calculate the Hamming distance between matrix R^k , R^* , R^l and R^r

$$d\left(R^{k},R^{*}\right) = \frac{1}{n^{2}}\sum_{i=1}^{n}\sum_{j=1}^{n}d\left(\widetilde{r}_{ij}^{k},\widetilde{r}_{ij}^{*}\right)$$
(5)

$$d\left(R^{k},R^{l}\right) = \frac{1}{n^{2}}\sum_{i=1}^{n}\sum_{j=1}^{n}d\left(\widetilde{r}_{ij}^{k},\widetilde{r}_{ij}^{l}\right)$$

$$\tag{6}$$

$$d\left(R^{k},R^{r}\right) = \frac{1}{n^{2}}\sum_{i=1}^{n}\sum_{j=1}^{n}d\left(\widetilde{r}_{ij}^{k},\widetilde{r}_{ij}^{r}\right)$$
(7)

Obtain the consequence of $d(\tilde{r}_{ij}^k, \tilde{r}_{ij}^*), d(\tilde{r}_{ij}^k, \tilde{r}_{ij}^l)$ and $d(\tilde{r}_{ij}^k, \tilde{r}_{ij}^r)$ by the following equation

$$d(\tilde{a}_1, \tilde{a}_2) = |\mu_{1L} - \mu_{2L}| + |\mu_{1U} - \mu_{2U}| + |v_{1L} - v_{2L}| + |v_{1U} - v_{2U}|$$
(8)

Step 4: Calculate the numerical value of the similarity to decision-maker d_k relative to the ideal alternative

$$c_k = \frac{d(R^k, R^l) + d(R^k, R^r)}{d(R^k, R^*) + d(R^k, R^l) + (R^k, R^r)} (k = 1, 2, 3 \cdots, q)$$
(9)

Step 5: Calculate the weight λ_k of decision-maker d_k by normalizing the numerical value of similarity

$$\lambda_k = c_k / \sum_{k=1}^m c_k \ (k = 1, 2, 3 \cdots q)$$
(10)

4.3. Calculation of Attribute Weights

Step 1: Determine the interval intuitionistic fuzzy multi-attribute decision matrix \tilde{R}_k of the alternatives provided by each DM in relation to the attribute;

Step 2: Normalize the decision matrix above;

The interval intuitionistic fuzzy multi-attribute decision matrix is assumed as $\widetilde{R} = (\widetilde{r}_{ij})_{n*m} = \left(\left[\mu_{ij}^L, \mu_{ij}^U \right], \left[v_{ij}^L, v_{ij}^U \right] \right)_{n*m}$, and there is a difference between the benefit criterion and the cost criterion in attribute types. Confirm the normalized interval intuitionistic fuzzy decision matrix $\widetilde{\overline{R}} = \left(\widetilde{\overline{r}}_{ij} \right)_{n*m} = \left(\left[\overline{\mu}_{ij}^L, \overline{\mu}_{ij}^U \right], \left[\overline{v}_{ij}^L, \overline{v}_{ij}^U \right] \right)_{n*m}$ by the following equation:

The expression of benefit indicators is shown as follows:

$$\begin{cases} \overline{\mu}_{ij}^{L} = \mu_{ij}^{L} / \sqrt{\sum_{i=1}^{n} \left((1 - v_{ij}^{U}) + (1 - v_{ij}^{L}) \right)^{2}} \\ \overline{\mu}_{ij}^{U} = \mu_{ij}^{U} / \sqrt{\sum_{i=1}^{n} \left((1 - v_{ij}^{U}) + (1 - v_{ij}^{L}) \right)^{2}} \\ \overline{\nu}_{ij}^{L} = 1 - (1 - v_{ij}^{L}) / \sqrt{\sum_{i=1}^{n} (\mu_{ij}^{L} + \mu_{ij}^{U})^{2}} \\ \overline{\nu}_{ij}^{U} = 1 - (1 - v_{ij}^{U}) / \sqrt{\sum_{i=1}^{n} (\mu_{ij}^{L} + \mu_{ij}^{U})^{2}} \end{cases}$$
(11)

The expression of cost indicators is shown as follows:

$$\begin{cases} \overline{\mu}_{ij}^{L} = (1 - v_{ij}^{L})^{-1} / \sqrt{\sum_{i=1}^{n} (1/\mu_{ij}^{U}) + (1/\mu_{ij}^{L})^{2}} \\ \overline{\mu}_{ij}^{U} = (1 - v_{ij}^{U})^{-1} / \sqrt{\sum_{i=1}^{n} (1/\mu_{ij}^{U}) + (1/\mu_{ij}^{L})^{2}} \\ \overline{v}_{ij}^{L} = 1 - (1/\mu_{ij}^{L}) / \sqrt{\sum_{i=1}^{n} ((1 - v_{ij}^{L})^{-1} + (1 - v_{ij}^{U})^{-1})^{2}} \\ \overline{v}_{ij}^{U} = 1 - (1/\mu_{ij}^{U}) / \sqrt{\sum_{i=1}^{n} ((1 - v_{ij}^{L})^{-1} + (1 - v_{ij}^{U})^{-1})^{2}} \end{cases}$$
(12)

Step 3: Utilize the aggregation operator to aggregate the normalized decision matrix with the weights of DMs;

Step 4: Each decision-maker provides a subjective preference value for the alternative; It is assumed that DMs have certain subjective preferences for alternatives $Y_i(i = 1, 2, 3 \cdots, m)$. Suppose that subjective preference can be described as interval intuitionistic fuzzy value $\tilde{\theta}_i = \langle [\alpha_{iL}, \alpha_{iU}], [\beta_{iL}, \beta_{iU}] \rangle$.

Step 5: Each subjective preference value is aggregated by the aggregation operator on the basis of DMs' weights;

Step 6: Establish an optimization model and conduct attribute weight vector by constructing the Lagrange function.

On account of the plentiful objective limitations in an authentic decision-making environment, there are customarily certain distinctions between the subjective preferences and objective preferences of DMs. Therefore, the deviation values of subjective preference and objective preference corresponding to decision-makers should be minimized.

For attributes $G_j(j = 1, 2, 3 \cdots n)$, the deviation value $d(\tilde{F}_{ij}, \tilde{\theta}_i)$ between subjective preference of DMs for alternative and the corresponding objective preference value is demonstrated as follows.

$$d(\widetilde{F}_{ij}, \widetilde{\theta}_i) = \frac{1}{4}\omega_j (|\mu_{ijL} - \alpha_{iL}| + |\mu_{ijU} - \alpha_{iU}| + |v_{ijL} - \beta_{iL}| + |v_{ijU} - \beta_{iU}|)$$

$$(i = 1, 2, 3 \cdots m; j = 1, 2, 3 \cdots n)$$
(13)

For attributes G_j ($j = 1, 2, 3 \cdots n$), the deviation between subjective and objective preference values of the DMs for all alternatives can be defined as:

$$D(\omega) = \sum_{i=1}^{m} d(\tilde{F}_{ij}, \tilde{\theta}_i) = \frac{1}{4} \sum_{i=1}^{m} \omega_j (|\mu_{ijL} - \alpha_{iL}| + |\mu_{ijU} - \alpha_{iU}| + |v_{ijL} - \beta_{iL}| + |v_{ijU} - \beta_{iU}|)$$
(14)

The deviation value between subjective preference and objective preference of DMs for all attributes of all alternatives can be demonstrated as:

$$D(\omega) = \sum_{j=1}^{n} D_{j}(\omega) = \frac{1}{4} \sum_{j=1}^{n} \sum_{i=1}^{m} \omega_{j} \left(\left| \mu_{ijL} - \alpha_{iL} \right| + \left| \mu_{ijU} - \alpha_{iU} \right| + \left| v_{ijL} - \beta_{iL} \right| + \left| v_{ijU} - \beta_{iU} \right| \right)$$
(15)

The attribute weight vector ω should be minimized as $D(\omega)$, which can be expressed as:

$$\min D(\omega) = \frac{1}{4} \sum_{j=1}^{n} \sum_{i=1}^{m} \omega_j (|\mu_{ijL} - \alpha_{iL}| + |\mu_{ijU} - \alpha_{iU}| + |v_{ijL} - \beta_{iL}| + |v_{ijU} - \beta_{iU}|)$$
(16)

Since the attribute weight is completely unknown, the following optimization model is established to ascertain the accurate value of attribute weight.

$$\begin{cases} \min D(\omega) = \frac{1}{4} \sum_{j=1}^{n} \sum_{i=1}^{m} \omega_{j} (|\mu_{ijL} - \alpha_{iL}| + |\mu_{ijU} - \alpha_{iU}| + |v_{ijL} - \beta_{iL}| + |v_{ijU} - \beta_{iU}|) \\ s.t. \sum_{j=1}^{n} \omega_{j}^{2} = 1, \omega_{j} \ge 0 (j = 1, 2, 3 \cdots, n) \end{cases}$$

$$(17)$$

The optimization model can be solved by constructing the Lagrange function:

$$L(\omega,\lambda) = \frac{1}{4} \sum_{j=1}^{n} \sum_{i=1}^{m} \omega_j \left(\left| \mu_{ijL} - \alpha_{iL} \right| + \left| \mu_{ijU} - \alpha_{iU} \right| + \left| v_{ijL} - \beta_{iL} \right| + \left| v_{ijU} - \beta_{iU} \right| \right) + \frac{\lambda}{8} \left(\sum_{i=1}^{n} \omega_j^2 - 1 \right)$$
(18)

By taking the partial derivative of the above equation and setting partial derivative equal to 0,

$$\begin{cases} \frac{\partial L}{\partial \omega_j} = \frac{1}{4} \sum_{i=1}^m \left(\left| \mu_{ijL} - \alpha_{iL} \right| + \left| \mu_{ijU} - \alpha_{iU} \right| + \left| v_{ijL} - \beta_{iL} \right| + \left| v_{ijU} - \beta_{iU} \right| \right) + \frac{1}{4} \lambda \omega_j = 0 \\ \frac{\partial L}{\partial \lambda} = \frac{1}{8} \left(\sum_{j=1}^n \omega_j^2 - 1 \right) = 0 \end{cases}$$

$$(19)$$

The attribute weight can be obtained by solving the above equation:

$$\omega_{j} = \frac{\sum_{i=1}^{m} \left(\left| \mu_{ijL} - \alpha_{iL} \right| + \left| \mu_{ijU} - \alpha_{iU} \right| + \left| v_{ijL} - \beta_{iL} \right| + \left| v_{ijU} - \beta_{iU} \right| \right)}{\sum_{j=1}^{n} \sum_{i=1}^{m} \left(\left| \mu_{ijL} - \alpha_{iL} \right| + \left| \mu_{ijU} - \alpha_{iU} \right| + \left| v_{ijL} - \beta_{iL} \right| + \left| v_{ijU} - \beta_{iU} \right| \right)}$$
(20)

4.4. Ranking of Alternatives

Step 1: Determine the positive-ideal solution Y^+ and the negative-ideal solution Y^- of the multi-attribute group decision problem according to the normalized multi-attribute group decision matrix;

$$Y^{+} = (Y_{1}^{+}, Y_{2}^{+}, \cdots, Y_{n}^{+}) = (\langle [\mu_{1L}^{+}, \mu_{1U}^{+}], [v_{1L}^{+}, v_{1U}^{+}] \rangle, \langle [\mu_{2L}^{+}, \mu_{2U}^{+}], [v_{2L}^{+}, v_{2U}^{+}] \rangle, \cdots, \langle [\mu_{nL}^{+}, \mu_{nU}^{+}], [v_{nL}^{+}, v_{nU}^{+}] \rangle)$$
(21)

$$Y^{-} = (Y_{1}^{+}, Y_{2}^{-}, \cdots, Y_{n}^{-}) = (\langle [\mu_{1L}^{-}, \mu_{1U}^{-}], [v_{1L}^{-}, v_{1U}^{-}] \rangle, \langle [\mu_{2L}^{-}, \mu_{2U}^{-}], [v_{2L}^{-}, v_{2U}^{-}] \rangle, \cdots, \langle [\mu_{nL}^{-}, \mu_{nU}^{-}], [v_{nL}^{-}, v_{nU}^{-}] \rangle)$$
(22)

Step 2: Obtain the values of group effect S_i and individual regret R_i of each alternative according to attribute weights;

$$S_{i} = \sum_{j=1}^{n} \omega_{j} \left[\frac{d(Y_{j}^{+}, \widetilde{F}_{ij})}{d(Y_{j}^{+}, Y_{j}^{-})} \right] \quad i = 1, 2, 3 \cdots, m$$
(23)

$$R_i = \max_j \left\{ \omega_j \left[\frac{d(Y_j^+, \widetilde{F}_{ij})}{d(Y_j^+, Y_j^-)} \right] \right\} \quad i = 1, 2, 3, \cdots, m$$
(24)

Step 3: Calculate compromise value of each alternative;

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*}, \quad i = 1, 2, 3, \cdots, m$$
(25)

 $S^* = \min_i S_i$; $S^- = \max_i S_i$; $R^* = \min_i R_i$; $R^- = \max_i R_i$; v is the coefficient of the decision-making mechanism, $v \in [0, 1]$; when v > 0.5, it denotes the decision-making mechanism according to maximum group utility; at the time when v = 0.5, it represents the processing procedure in accordance with the decision mechanism reached by the decision-makers through consultation; if v < 0.5, it means conducting decisions according to the decision-making mechanism with the smallest individual regret.

Step 4: Effect value on the group S_i ; individual regret value R_i ; and compromise value Q_i were sorted from the smallest to the largest to determine the compromise alternative. Assume the ranking obtained by increasing values Q_i is $Y^{(1)}, Y^{(2)}, \dots Y^{(J)}, \dots Y^{(m)}$, then in terms of ranking condition 1 and ranking condition 2, the alternatives' final ranking is able to confirmed.

Ranking Condition 1. *Receivable advantage condition:* $Q(Y^{(2)}) - Q(Y^{(1)}) \ge \frac{1}{m-1}$.

Ranking Condition 2. *Receivable stability condition: alternative* $Y^{(1)}$ *ought to be the one ranked at the first place by values of* S_i *and* R_i .

If ranking condition 1 and ranking condition 2 are satisfied at the same time, then the alternative $Y^{(1)}$ is also the stable and optimal solution during the decision process.

If ranking condition 1 and ranking condition 2 are not satisfied at the same time, when ranking condition 1 is satisfied and ranking condition 2 is unsatisfied, both alternative $Y^{(1)}$ and alternative $Y^{(2)}$ are compromised alternatives. In the case that ranking condition 1 is unsatisfied, obtaining the largest J by $Q_i(Y^{(J)}) - Q_i(Y^{(1)}) \le \frac{1}{m-1}$, then $Y^{(1)}, Y^{(2)}, \dots Y^{(J)}, \dots Y^{(m)}$ are compromised alternatives.

5. Numerical Case Analysis

In this section, five alternative sites of a manufacturing industrial park including $Y^{(1)}, Y^{(2)}, \dots Y^{(5)}$ are evaluated to inspect the validity and availability of the framework. First of all, a comprehensive criteria system with a foundation of literature studies and relevant research reports is established. Then, four DMs $D_t(t = 1, 2, \dots, 4)$, which have different industry backgrounds, are invited and organized as an evaluation team. Two equipment purchasers of the group have different demands of device quantity and represent potential customers of the manufacturing industrial park. The professor in the evaluation team has abundant theoretical knowledge and the marketing staff have affluent experience in the domain of marketing. This is based on the actual situation and experience of their own, and in the meantime, they consider the complexity and ambiguity of the realistic decision-making environment. Four DMs apply interval intuitionistic fuzzy values to make performing assessments of five qualitative or quantitative criteria corresponding to the five alternatives. Thereafter, according to the evaluation information provided by the DMs, alternatives are assessed and ranked according to the proposed model.

5.1. Establish a Multi-Attribute Evaluation System

According to the relevant literature analysis, a comprehensive evaluation criteria system is established, as is demonstrated in Table 1.

Table 1. Evaluation criteria system summarized from the aggregation of interrelated literature for site selection.

Criteria	Sub-Criteria	Preferred
	Emission of greenhouse gases	Minimization
	Industrial electricity consumption	Minimization
Environmental conditions	Industrial noise pollution	Minimization
	Production of industrial waste material	Minimization
	Industrial wastewater drainage	Minimization
	Level of consumption	Maximization
	Income level	Maximization
Economic characteristics	Human resource condition	Maximization
	Return on investment	Maximization
	Perfection of public facilities	Maximization
	Proximity to commercial activities	Maximization
	Comply with sustainable laws	Maximization
Social factors	Administrative district size	Maximization
	Population density	Maximization
	Population growth rate	Maximization
	Terrain advantage	Maximization
	Road patency	Maximization
Traffic factors	Service capacity	Maximization
	Number of roads	Maximization
	Service radius	Maximization
	Site preparation cost	Minimization
	Construction investment costs	Minimization
Operating conditions	Operation and management costs	Minimization
-	Tax costs	Minimization
	Number of competitors	Minimization

Maximization indicates the larger the sub-criterion value is, the better the criterion will be. Minimization indicates the smaller the sub-criterion value is, the better the criterion will be.

5.2. Determine Decision-Maker Weights

Step 1: Four experts evaluate the five alternatives, and each expert provides preference information for the pairwise comparison of the corresponding alternatives. We then form the interval intuitionistic fuzzy preference relation R_m ($m = 1, \dots 4$);

```
R_{1} = \begin{pmatrix} ([0.50, 0.50], [0.50, 0.50]) & ([0.40, 0.50], [0.20, 0.30]) & ([0.20, 0.30], [0.50, 0.60]) & ([0.40, 0.50], [0.10, 0.30]) & ([0.20, 0.40], [0.40, 0.50]) \\ ([0.20, 0.30], [0.40, 0.50]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.30, 0.40], [0.40, 0.50]) & ([0.40, 0.50], [0.30, 0.40]) & ([0.20, 0.40], [0.30, 0.50]) \\ ([0.50, 0.60], [0.20, 0.30]) & ([0.40, 0.50], [0.30, 0.40]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.60, 0.70], [0.10, 0.20]) & ([0.30, 0.40], [0.20, 0.30]) \\ ([0.10, 0.30], [0.40, 0.50]) & ([0.30, 0.40], [0.40, 0.50]) & ([0.10, 0.20], [0.60, 0.70]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.40, 0.50], [0.20, 0.30]) \\ ([0.40, 0.50], [0.20, 0.40]) & ([0.30, 0.50], [0.20, 0.40]) & ([0.30, 0.50], [0.30, 0.40]) & ([0.20, 0.30], [0.40, 0.50]) & ([0.40, 0.50], [0.20, 0.30]) \\ ([0.40, 0.50], [0.20, 0.40]) & ([0.30, 0.50], [0.20, 0.30]) & ([0.20, 0.30], [0.50, 0.70]) & ([0.40, 0.50], [0.10, 0.20]) & ([0.20, 0.30], [0.40, 0.50]) \\ ([0.20, 0.30], [0.30, 0.50]) & ([0.30, 0.50], [0.20, 0.30]) & ([0.20, 0.30], [0.50, 0.70]) & ([0.40, 0.50], [0.30, 0.40]) & ([0.20, 0.30], [0.40, 0.50]) \\ ([0.20, 0.30], [0.30, 0.50]) & ([0.30, 0.50], [0.20, 0.30]) & ([0.20, 0.40], [0.40, 0.50]) & ([0.30, 0.40]) & ([0.20, 0.30], [0.40, 0.50]) \\ ([0.20, 0.30], [0.30, 0.50]) & ([0.30, 0.50], [0.50, 0.50]) & ([0.20, 0.40], [0.40, 0.50]) & ([0.30, 0.40]) & ([0.20, 0.40], [0.30, 0.50]) \\ ([0.50, 0.70], [0.20, 0.30]) & ([0.40, 0.50], [0.20, 0.40]) & ([0.50, 0.50]) & ([0.50, 0.70], [0.10, 0.20]) & ([0.30, 0.40], [0.20, 0.50]) \\ ([0.10, 0.20], [0.40, 0.50]) & ([0.30, 0.40], [0.30, 0.50]) & ([0.10, 0.20], [0.50, 0.50]) & ([0.30, 0.40], [0.20, 0.30]) \\ ([0.40, 0.50], [0.20, 0.50]) & ([0.30, 0.40], [0.30, 0.50]) & ([0.10, 0.20], [0.50, 0.50]) & ([0.50, 0.50]) & ([0.40, 0.50], [0.20, 0.30]) \\ ([0.40, 0.50], [0.20, 0.50]) & ([0.30, 0.40], [0.30, 0.50]) & ([0.20, 0.50]) & ([0.50, 0.50]) & ([0.40, 0.50]) & ([0.20, 0.50]) \\ ([0.40, 0.50], [0.20, 0.50]) & ([0.30, 0.50], [0.20, 0.40]) & ([0.20, 0.50], [0.30, 0.40]) & ([0.20, 0.30], [0.40, 0.50]) & ([0.50,
```

```
R_{3} = \begin{pmatrix} ([0.50, 0.50], [0.50, 0.50]) & ([0.20, 0.30], [0.40, 0.50]) & ([0.30, 0.60], [0.20, 0.40]) & ([0.30, 0.40], [0.40, 0.50]) & ([0.50, 0.60], [0.20, 0.30]) \\ ([0.40, 0.50], [0.20, 0.30]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.10, 0.40], [0.40, 0.50]) & ([0.20, 0.40], [0.30, 0.50]) & ([0.10, 0.40], [0.30, 0.50]) \\ ([0.20, 0.40], [0.30, 0.60]) & ([0.40, 0.50], [0.10, 0.40]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.60, 0.70], [0.10, 0.20]) & ([0.30, 0.40], [0.50, 0.60]) \\ ([0.40, 0.50], [0.30, 0.40]) & ([0.30, 0.50], [0.20, 0.40]) & ([0.10, 0.20], [0.60, 0.70]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.40, 0.50], [0.20, 0.40]) \\ ([0.20, 0.30], [0.50, 0.60]) & ([0.30, 0.50], [0.30, 0.40]) & ([0.50, 0.60], [0.30, 0.40]) & ([0.20, 0.40], [0.40, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50]) & ([0.50, 0.50])
```

Step 2: Build the PID matrix *R*^{*} as follows:

$$R_{*} = \begin{pmatrix} ([0.50, 0.50], [0.50, 0.50]) & ([0.325, 0.45], [0.275, 0.375]) & ([0.275, 0.45], [0.35, 0.525]) & ([0.35, 0.45], [0.25, 0.375]) & ([0.35, 0.475], [0.275, 0.40]) \\ ([0.275, 0.375], [0.325, 0.45]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.175, 0.40], [0.40, 0.50]) & ([0.275, 0.45], [0.30, 0.425]) & ([0.175, 0.40], [0.30, 0.50]) \\ ([0.35, 0.525], [0.275, 0.45]) & ([0.40, 0.50], [0.175, 0.40]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.575, 0.70], [0.10, 0.20]) & ([0.375, 0.55]) \\ ([0.25, 0.375], [0.35, 0.45]) & ([0.30, 0.425], [0.275, 0.45]) & ([0.10, 0.20], [0.575, 0.70]) & ([0.50, 0.50], [0.50, 0.50]) & ([0.375, 0.50], [0.20, 0.325]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.175, 0.40]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.20, 0.325], [0.375, 0.375]) & ([0.50, 0.50], [0.50, 0.50]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.175, 0.40]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.20, 0.325], [0.375, 0.375]) & ([0.50, 0.50], [0.50, 0.50]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.175, 0.40]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.20, 0.325], [0.375, 0.375]) & ([0.50, 0.50], [0.50, 0.50]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.175, 0.40]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.20, 0.325], [0.375, 0.375]) & ([0.50, 0.50], [0.50, 0.50]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.175, 0.40]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.20, 0.325], [0.375, 0.375]) & ([0.50, 0.50], [0.50, 0.50]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.175, 0.40]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.20, 0.325], [0.375, 0.375]) & ([0.50, 0.50], [0.50, 0.50]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.175, 0.40]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.20, 0.325], [0.375, 0.375]) & ([0.50, 0.50], [0.50, 0.50]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.175, 0.40]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.20, 0.325], [0.375, 0.375]) & ([0.50, 0.50], [0.50, 0.50]) \\ ([0.275, 0.40], [0.35, 0.475]) & ([0.30, 0.50], [0.50, 0.50]) & ([0.375, 0.55], [0.30, 0.40]) & ([0.375, 0$$

Step 3: Build the L-NID matrix R^l and R-NID matrix R^r as follows:

$$\begin{split} R^{l} &= \left(\tilde{r}^{l}_{ij} \right)_{5 \times 5} \\ &= \left[\begin{array}{c} ([0.50, 0.50], [0.50, 0.50])([0.20, 0.30], [0.40, 0.50])([0.20, 0.30], [0.50, 0.70])([0.30, 0.40], [0.40, 0.50])([0.20, 0.30], [0.40, 0.50]) \\ ([0.20, 0.30], [0.40, 0.50])([0.50, 0.50], [0.50, 0.50])([0.10, 0.40], [0.40, 0.50])([0.20, 0.40], [0.30, 0.40])([0.10, 0.40], [0.30, 0.50]) \\ ([0.20, 0.40], [0.40, 0.60])([0.40, 0.50], [0.10, 0.40])([0.50, 0.50], [0.50, 0.50])([0.60, 0.70], [0.10, 0.20])([0.30, 0.50], [0.50, 0.60]) \\ ([0.10, 0.20], [0.40, 0.50])([0.30, 0.40], [0.40, 0.50])([0.10, 0.20], [0.60, 0.70])([0.50, 0.50], [0.50, 0.50])([0.30, 0.50], [0.20, 0.40]) \\ ([0.10, 0.30], [0.50, 0.60])([0.30, 0.50], [0.20, 0.40])([0.20, 0.50], [0.30, 0.40])([0.20, 0.30], [0.40, 0.50])([0.50, 0.50]) \\ ([0.10, 0.30], [0.50, 0.60])([0.30, 0.50], [0.20, 0.40])([0.20, 0.50], [0.30, 0.40])([0.20, 0.30], [0.40, 0.50])([0.50, 0.50])([0.50, 0.50]) \\ ([0.10, 0.30], [0.50, 0.60])([0.30, 0.50], [0.20, 0.40])([0.20, 0.50], [0.30, 0.40])([0.20, 0.30], [0.40, 0.50])([0.50, 0.50])([0.50, 0.50]) \\ ([0.10, 0.30], [0.50, 0.60])([0.30, 0.50], [0.20, 0.40])([0.20, 0.50], [0.30, 0.40])([0.20, 0.30], [0.40, 0.50])([0.50, 0.5$$

 $R^{r} = \left(\tilde{r}_{ij}^{l}\right)_{5\times5} \\ = \begin{bmatrix} ([0.50, 0.50], [0.50, 0.50])([0.40, 0.50], [0.20, 0.30])([0.40, 0.60], [0.20, 0.40])([0.40, 0.50], [0.10, 0.20])([0.50, 0.60], [0.10, 0.30]) \\ ([0.40, 0.50], [0.20, 0.30])([0.50, 0.50], [0.50, 0.50])([0.30, 0.40], [0.40, 0.50])([0.40, 0.50], [0.30, 0.40])([0.20, 0.40], [0.30, 0.50]) \\ ([0.50, 0.70], [0.20, 0.30])([0.40, 0.50], [0.10, 0.40])([0.50, 0.50], [0.50, 0.50])([0.60, 0.70], [0.10, 0.20])([0.30, 0.40], [0.20, 0.50]) \\ ([0.40, 0.50], [0.30, 0.40])([0.30, 0.50], [0.20, 0.40])([0.10, 0.20], [0.50, 0.50])([0.50, 0.50], [0.50, 0.50])([0.40, 0.50], [0.20, 0.30]) \\ ([0.40, 0.50], [0.20, 0.30])([0.30, 0.50], [0.10, 0.40])([0.50, 0.60], [0.30, 0.40])([0.20, 0.40], [0.30, 0.50])([0.50$

Step 4: Calculate the Hamming distance of the interval intuitionistic fuzzy preference relation between R^k (k = 1, 2, 3, 4) and R^* , R^l and R^r , respectively. The results are shown as follows:

$d(R^1, R^*) = 0.164,$	$d(R^1, R^l) = 0.212,$	$d(R^1, R^r) = 0.212,$
$d(R^2, R^*) = 0.180,$	$d(R^2, R^l) = 0.212,$	$d(R^2, R^r) = 0.212,$
$d(R^3, R^*) = 0.196,$	$d(R^3, R^l) = 0.204,$	$d(R^3, R^r) = 0.204,$
$d(R^4, R^*) = 0.176,$	$d(R^4, R^l) = 0.196,$	$d(R^4, R^r) = 0.204,$

Step 5: Calculate the closeness degree of each expert relative to the ideal alternative;

$$c_1 = 0.7211$$
 $c_2 = 0.7020$ $c_3 = 0.6755$ $c_4 = 0.6944$

Step 6: The weight of experts D_k is obtained by planning the closeness degree, which is: $\lambda_1 = 0.2582$ $\lambda_2 = 0.2513$ $\lambda_3 = 0.2419$ $\lambda_4 = 0.2486$.

5.3. Determine Attribute Weights

DMs $\widetilde{d}_k(k = 1, 2, 3, 4)$ apply the interval intuitionistic fuzzy decision matrix \widetilde{R}_k to describe the feature vectors of the site-selection alternative $Y_i = \{Y_1, Y_2, \dots, Y_5\}$ within the corresponding criteria $G_i = \{g_1, g_2 \dots g_5\}$.

$$\begin{split} \widetilde{R}_1 = \begin{pmatrix} g_1 & g_1 & g_2 & g_1 & g_1 & g_2 & g_1 & g_$$

(1) Apply the formula to normalize the decision matrixes, and the normalized decision matrix

 R_k is obtained. The results of the normalized decision matrixes are shown in Appendix A.

(2) The normalized decision matrix is aggregated by the aggregation operator according to the weight of decision-makers, and the comprehensive evaluation matrix R is shown as follows:

$$R = \begin{pmatrix} g_1 & g_2 & g_3 & g_4 & g_5 \\ y_1 & \begin{bmatrix} 0.17157, 0.20152 \\ 0.54741, 0.67457 \end{bmatrix} & \begin{bmatrix} 0.15141, 0.18585 \\ 0.65206, 0.69008 \end{bmatrix} & \begin{bmatrix} 0.17289, 0.20351 \\ 0.65462, 0.71913 \end{bmatrix} & \begin{bmatrix} 0.14663, 0.18208 \\ 0.67614, 0.74137 \end{bmatrix} & \begin{bmatrix} 0.12615, 0.16356 \\ 0.55848, 0.72506 \end{bmatrix} \end{pmatrix}$$

$$y_2 & \begin{bmatrix} 0.12595, 0.14637 \\ 0.70363, 0.79012 \end{bmatrix} & \begin{bmatrix} 0.10598, 0.16624 \\ 0.71239, 0.74963 \end{bmatrix} & \begin{bmatrix} 0.11472, 0.16138 \\ 0.68815, 0.73169 \end{bmatrix} & \begin{bmatrix} 0.13984, 0.18913 \\ 0.66663, 0.71875 \end{bmatrix} & \begin{bmatrix} 0.12028, 0.25295 \\ 0.45091, 0.68510 \end{bmatrix} \end{pmatrix}$$

$$y_3 & \begin{bmatrix} 0.13013, 0.14689 \\ 0.57847, 0.68955 \end{bmatrix} & \begin{bmatrix} 0.12802, 0.18032 \\ 0.67067, 0.71903 \end{bmatrix} & \begin{bmatrix} 0.13601, 0.21127 \\ 0.65769, 0.70001 \end{bmatrix} & \begin{bmatrix} 0.08938, 0.13985 \\ 0.66567, 0.74020 \end{bmatrix} & \begin{bmatrix} 0.12740, 0.14892 \\ 0.65743, 0.73878 \end{bmatrix} & \begin{bmatrix} 0.12740, 0.14892 \\ 0.657444, 0.75228 \end{bmatrix} \end{pmatrix}$$

$$y_4 & \begin{bmatrix} 0.13372, 0.16656 \\ 0.68868, 0.75693 \end{bmatrix} & \begin{bmatrix} 0.15149, 0.19471 \\ 0.63387, 0.67067 \end{bmatrix} & \begin{bmatrix} 0.12654, 0.16723 \\ 0.65667, 0.74020 \end{bmatrix} & \begin{bmatrix} 0.14719, 0.19633 \\ 0.63672, 0.67608 \end{bmatrix} & \begin{bmatrix} 0.12576, 0.13393 \\ 0.58594, 0.71532 \end{bmatrix} \end{pmatrix}$$

$$y_5 & \begin{bmatrix} 0.13399, 0.15779 \\ 0.66550, 0.76691 \end{bmatrix} & \begin{bmatrix} 0.11856, 0.17050 \\ 0.63387, 0.71196 \end{bmatrix} & \begin{bmatrix} 0.10662, 0.19965 \\ 0.68815, 0.72993 \end{bmatrix} & \begin{bmatrix} 0.12677, 0.70558 \\ 0.65617, 0.70558 \end{bmatrix} & \begin{bmatrix} 0.11559, 0.13017 \\ 0.68983, 0.73732 \end{bmatrix} \end{pmatrix}$$

- (3) The DMs provide a subjective preference value of alternatives, and the aggregation operator is used to aggregate according to the weight of DMs, and then comprehensive subjective preference value is obtained as: $\tilde{\theta}_i = ([0.3261, 0.5137], [0.2950, 0.4207]).$
- (4) Calculate the attribute weight ω_i according to the formula of the attribute weight:

 $\omega_i = (0.2019, 0.1999, 0.2025, 0.2019, 0.1937)$

5.4. Ranking the Alternative

 Determine the positive-ideal solution Y⁺ and negative-ideal solution Y⁻ on the grounds of comprehensive evaluation matrix

$$\begin{split} Y^{+} &= \left(\begin{array}{c} [0.17157, 0.20152], \\ [0.54741, 0.67457] \\ Y^{-} &= \left(\begin{array}{c} [0.12595, 0.14637], \\ [0.70363, 0.79012] \end{array} \right), \left(\begin{array}{c} [0.15149, 0.19471], \\ [0.63387, 0.67067] \\ [0.10598, 0.16624], \\ [0.71239, 0.74963] \end{array} \right), \left(\begin{array}{c} [0.17289, 0.21127], \\ [0.65462, 0.70001] \\ [0.65462, 0.70001] \end{array} \right), \left(\begin{array}{c} [0.14719, 0.19633], \\ [0.63672, 0.67608] \\ [0.63872, 0.67608] \end{array} \right) \left(\begin{array}{c} [0.12740, 0.25295], \\ [0.45091, 0.68510] \\ [0.45091, 0.68510] \\ [0.71239, 0.74963] \end{array} \right), \left(\begin{array}{c} [0.10662, 0.16138], \\ [0.71239, 0.74963] \end{array} \right), \left(\begin{array}{c} [0.10662, 0.16138], \\ [0.68815, 0.74020] \end{array} \right), \left(\begin{array}{c} [0.08938, 0.13985], \\ [0.67614, 0.74137] \end{array} \right) \left(\begin{array}{c} [0.11559, 0.13017], \\ [0.68983, 0.75228] \end{array} \right) \right) \right) \right) \right) \\ \end{array}$$

(2) Calculate the values of group effect S_i and individual regret R_i to the alternatives; the outcomes are displayed in Table 2.

Table 2. The ranking results of selected alternatives.

	Y_1	<i>Y</i> ₂	Y ₃	Y_4	Y_5	Ranking
S_i	2.0777	1.8373	0.8164	0.4534	0.7854	$Y_4 \succ Y_5 \succ Y_3 \succ Y_2 \succ Y_1$
R_i	9.3646	6.0417	1.4583	1.1085	1.7292	$Y_4 \succ Y_3 \succ Y_5 \succ Y_2 \succ Y_1$
Q_i	1.0000	0.7248	0.1328	0.0000	0.1398	$Y_4 \succ Y_3 \succ Y_5 \succ Y_2 \succ Y_1$

Ranking the merits of the alternative position Y_i according to the Q_i value from small to large: $Y_4 \succ Y_3 \succ Y_5 \succ Y_2 \succ Y_1$, according to ranking condition 1 and ranking condition 2, it can be concluded that Y_2 , Y_5 are compromised alternatives.

6. Performance Analysis

A comparative analysis of several MCDM techniques and a sensitivity analysis with respect to criteria weights and DMs weights are implemented to inspect the robustness of the method.

6.1. Comparison Analysis

A discussion of ranking consequences is shown through the application of other universally used fuzzy MCDM methods, for example, TOPSIS, PROMETHEE and GRA. With an intense willing to understand and compare the models conveniently, the calculation results are described as crisp values. Ranking results based on the above four fuzzy models are shown in Table 3.

	Proposed Method	Ranking	TOPSIS	Ranking	PROMETHEE	Ranking	GRA	Ranking
Y_1	1.0000	5	0.1519	5	-0.0423	5	0.1114	5
Y_2	0.7248	4	0. 2438	3	-0.0375	4	0.1816	4
Y_3	0.1328	2	0.2816	2	-0.0026	2	0.2309	2
Y_4	0.0000	1	0.3518	1	0.0276	1	0.2460	1
Y_5	0.1398	3	0. 1802	4	-0.0194	3	0.2302	3

Table 3. Ranking results of diverse MCDM methods.

Table 3 shows a comparison of results obtained by the proposed method and other multi-attribute ranking methods. Among them, the ranking results obtained by the PROMETHEE method and fuzzy GRA method are consistent, which are: $Y_4 \succ Y_3 \succ Y_5 \succ Y_2 \succ Y_1$. The ranking results obtained by the fuzzy TOPSIS method are slightly different, which are shown as: $Y_4 \succ Y_3 \succ Y_2 \succ Y_5 \succ Y_1$. According to the results, the sorting consequences of the proposed method are basically in the same order as those obtained by the other three methods, excepting the alternative of Y_2 ; Y_5 . The comparison results show that Y_4 is still the first-rank alternative and Y_1 is the worst alternative. The outcomes illustrate the proposed method has favorable robustness.

In addition, other advantages of the proposed method are explained as follows. Firstly, the modified TOPSIS method is applied to determine the weight of decision-makers. Compared with processing methods such as assigning the weight of the decision-maker directly or assigning the importance of the decision-maker according to the network analysis method (ANP), this measure can effectively overcome the effect of the subjective arbitrariness of the decision-maker on the final ranking result. Secondly, the VIKOR method based on the distance measure is applied to rank and selects the best alternatives. This method effectively takes into account the influence of interaction between alternatives and maximizes the group benefit, and the optimal compromise alternative is obtained by minimizing the individual regret value of opposing opinions. Therefore, the proposed method is full of benefits and can be extended and applied to solve practical problems.

6.2. Sensitivity Analysis

For the purpose of finding out the influence of changes in criteria weights with respect to the eventual ranking result, entire alternatives' ranking index values are recalculated with 20% less weight and more weight compared to baseline weight. When one of the criteria weights is decreased or increased, the rest of the criteria will be adjusted to ensure the sum of overall weights is equal to 1.

Assuming the original weight of the kth criterion is w_k , when it decreases or increases by 20%, then w_k is translated into w'_k , where $w'_k = \alpha w_k$. Values of α are 80% or 120%, and other criteria weights are changed to $w'_m = \beta w_m$ ($m \neq k, m = 1, 2, ..., M$), where conditions on changed weights of criteria are satisfied, namely, $\alpha w_k + \sum_{m=1,m\neq k}^{M} \beta w_m = 1$, where $\beta = \frac{1 - \alpha w_k}{1 - w_k}$. Then, the value of β and the whole weights can be calculated. On the foundation of carrying out experiments in accordance with five criteria, the assessments of five aspects—economic characteristics, environmental conditions, social factors, operating conditions and traffic factors—are generated, and the representative results are displayed in Table 4.

Table 4. Sensitivity analysis of alternative ranking on the basis of fluctuation in the weights of criteria.

	w_1	w'_1	w_2	w'_2	w_3	w'_3	w_4	w'_4	w_5	w'_5
Y ₁	5	5	5	5	5	5	5	5	5	5
Y_2	3	4	4	4	3	4	4	4	4	4
Y_3	2	2	2	3	2	2	3	2	3	2
Y_4	1	1	1	1	1	1	1	1	1	1
Y_5	4	3	3	2	4	3	2	3	2	3

With the purpose of figuring out the impact of DMs' weight changes on final ranking, we performed sensitivity analysis from eight scenarios corresponding to four DMs. In the context of the first scenario (S_1), the weight of DM_1 is increased to 110%, and the weights of the other DMs are decreased to 90%. Within the second scenario (S'_1), the weight of DM_1 is decreased to 90%, and at the same time, other DMs' weights are increased to 110%. After this, we performed identical procedures with other DMs. Eventually, there were changes in the final ranking result, which can be observed in Table 5.

Table 5. Sensitivity analysis in alternative ranking on the basis of fluctuation in the weights of DMs.

	<i>S</i> ₁	S'_1	<i>S</i> ₂	S'_2	S ₃	<i>S</i> ′ ₃	S_4	S'_4	S ₀
A_1	5	5	5	5	5	5	5	5	5
A_2	3	4	3	4	4	3	3	3	4
A_3	2	2	2	2	2	2	2	2	2
A_4	1	1	1	1	1	1	1	1	1
A_5	4	3	4	3	3	4	4	4	3

According to Table 5, the acquired assessment results are ingenious to DMs in four scenarios. When the weight of DM_1 or DM_2 is increased to 110%, other DMs' weights are decreased to 90%. There is also another phenomenon in which when the weight of DM_3 or DM_4 is decreased to 90%, the weights of other DMs will increase to 110%. On the basis of the four examples above, we illustrate that the best and the worst alternatives are stable and still the specific alternatives are in the original order. The initial alternative A_5 is better than alternative A_2 , but as for now, alternative A_2 is better than alternative A_5 .We can draw the conclusion that the ranking of A_2 and A_5 has changed. Nevertheless, the order of other alternatives remains unchanged, which repeatedly confirms the reliability of the proposed method.

7. Conclusions

With ambitions of achieving carbon peaking and carbon neutralization, intelligent energy-efficient manufacturing has attracted continuous attention from all sectors of society. In the face of the new campaign, manufacturing industrial parks should accelerate the realization of low-carbon development, make contributions to sustainable development, and promote the construction of industrial parks as well as the realization of the strategic goal of "dual carbon". For the purpose of accomplishing the set goals effectively and efficiently, it is necessary to establish an optimization model for selecting a suitable intelligent manufacturing industrial park location to assist manufacturing companies in improving their environmental performance, economic efficiency and market competitiveness.

This essay presents a three-phase fuzzy multi-criteria group decision-making framework to resolve the issue of suitable intelligent manufacturing industrial park location selection. The proposed framework is practical and can be applied to address other locationselection problems effectively. The conclusions are displayed as follows.

- (1) The high-end manufacturing industry, represented by intelligent and energy-saving manufacturing, is not only the inevitable way to transform and upgrade the manufacturing industry but is also the key to rebuilding the competitiveness and sustainability of the manufacturing industry. According to analysis of relevant literature research, we can draw the conclusion that the location of an intelligent energy-efficient manufacturing industrial park has higher requirements for environmental conditions, such as the emission of greenhouse gases, industrial electricity consumption, industrial noise pollution, production of industrial waste material and industrial wastewater drainage.
- (2) With the purposes of resolving ambiguity and uncertainty of information, intervalvalued intuitionistic fuzzy sets are applied to the problem-solving procedure. IIVFSs are applied to depict the preference information of decision-makers and an evaluation value is determined by the DMs for the attributes in the scheme. Finally, in terms of the concept of IIFS, interval intuitionistic fuzzy values are used for alternative rankings to ensure the accuracy and authenticity of the results.
- (3) A comprehensive location-selection criteria system covering the main attributes, including quantitative and qualitative criteria, is established, which can be implemented to evaluate the suitable location of an energy-saving intelligent manufacturing industrial park based on economic characteristics, environmental conditions, social factors, operating conditions and traffic factors, under the precondition of sustainable development.
- (4) The framework combining the fuzzy TOPSIS and fuzzy VIKOR methods is established to settle the low-carbon and intelligent manufacturing industrial park locationselection problem. The ranking model takes full consideration of the fuzzy preference judgment matrix's excellent characteristics and its preference information; at the same time, it also greatly reserves the calculation accuracy. Furthermore, the model neglects numerous unnecessary intermediate processes, leading to much more concise and reasonable outcomes.
- (5) The weights of attributes and decision-makers are calculated by the corresponding mathematical methods. To some extent, this quantitative analysis process can effectively reduce the influence of subjective factors or objective data errors on the results of the final ranking.
- (6) According to performance analysis, the sensitivity and contrastive analysis were performed relative to criteria and DM's weights, and the result verifies the robustness and feasibility of the proposed framework. The outcome shows that the proposed method is robust and effective for solving the issue of location selection. Based on the result, the most suitable location for establishing a manufacturing industrial park can be confirmed.

Prospective work in the area of optimal site selection for intelligent and sustainable manufacturing industrial parks can be carried out to ameliorate the availability of research. The following are some possible extensions. First of all, the proposed decision model can be extended to determine suitable sites for the development of other industrial parks (e.g., logistics industrial park or textile industrial park). Secondly, we can establish an evaluation criteria system according to particular research objectives and the needs of current consumers. Therefore, rearranging the criteria system with respect to developments in prospective research is essential. Thirdly, selecting and determining the specific amounts of DMs on the basis of concrete problems, as results lead from appropriate DMs, can be much more reasonable. Last but not least, other advanced MCDM methods such as: Decision-Making Trial and Evaluation Laboratory (DEMATEL) and weighted aggregated sum product assessment ((WASPAS) are supposed to solve site-selection problems, as demonstrated in further research by other research fellows.

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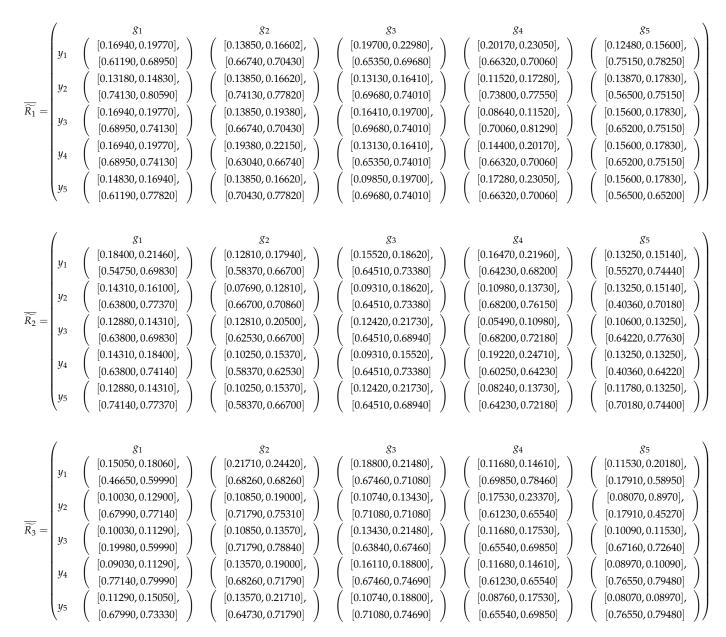
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Appendix A

Results of normalized decision matrixes.



	(<i>g</i> 1	<i>g</i> ₂	83	84	85
	11.	([0.18400, 0.21460],)	([0.13850, 0.16602],	([0.15520, 0.18620],)	([0.11680, 0.14610],)	([0.13250, 0.15140],)
	<i>y</i> 1	[0.54750, 0.69830]	[0.66740, 0.70430]	[0.64510, 0.73380]	[0.69850, 0.78460]	[0.55270, 0.74440]
	1/-	([0.13180, 0.14830],	([0.10850, 0.19000],)	([0.13130, 0.16410],)	([0.17530, 0.23370],	([0.13870, 0.17830],)
	<i>y</i> ₂	[0.74130, 0.80590]	[0.71790, 0.75310]	[0.69680, 0.74010]	[0.61230, 0.65540]	[0.56500, 0.75150]
$\overline{\widetilde{R_4}} =$		([0.12880, 0.14310],	([0.13850, 0.19380],)	([0.12420, 0.21730],)	([0.11680, 0.17530],)	([0.15600, 0.17830],)
	y_3	[0.63800, 0.69830]	[0.66740, 0.70430]	[0.64510, 0.68940]	[0.65540, 0.69850]	[0.65200, 0.75150]
	11.	([0.14310, 0.18400],)	([0.19380, 0.22150],)	([0.13130, 0.16410],)	([0.14400, 0.20170],	([0.13250, 0.13250],)
	<i>y</i> 4	[0.63800, 0.74140]	([0.63040, 0.66740])	[0.65350, 0.74010]	[0.66320, 0.70060]	[0.40360, 0.64220]
	1/-	([0.14830, 0.16940],	([0.10250, 0.15370],)	([0.09850, 0.19700],)	([0.17280, 0.23050],	([0.11780, 0.13250],)
	$\begin{pmatrix} y_5 \end{pmatrix}$	([0.61190, 0.77820])	([0.58370, 0.66700])	[0.69680, 0.74010]	[0.66320, 0.70060]	([0.70180, 0.74400]))

References

- 1. Önüt, S.; Efendigil, T.; Kara, S.S. A combined fuzzy MCDM method for selecting shopping center site: An example from Istanbul, Turkey. *Expert Syst. Appl.* **2010**, *37*, 1973–1980. [CrossRef]
- Yin, S.; Zhang, N.; Ullah, K.; Gao, S. Enhancing Digital Innovation for the Sustainable Transformation of Manufacturing Industry: A Pressure-State-Response System Framework to Perceptions of Digital Sustainable Innovation and Its Performance for Sustainable and Intelligent Manufacturing. Systems 2022, 10, 72. [CrossRef]
- 3. Mejía, G.; Montoya, C.; Bolívar, S.; Rossit, D.A. Job shop rescheduling with rework and reconditioning in Industry 4.0: An event-driven approach. *Int. J. Adv. Manuf. Technol.* **2022**, *119*, 3729–3745. [CrossRef]
- 4. Yin, S.; Zhang, N. Enhancing engineering ethics education (EEE) for Sustainable intelligent manufacturing: Implementation performance evaluation of core mechanism of Sustainable intelligence EEE. *Front. Psychol.* **2022**, *13*, 926133. [CrossRef]
- 5. Zhang, Y.; Wei, H.H.; Zhao, D.; Han, Y.; Chen, J. Understanding innovation diffusion and adoption strategies in megaproject networks through a fuzzy system dynamic model. *Front. Eng. Manag.* **2021**, *8*, 32–47. [CrossRef]
- 6. Radwan, N.M.; Elstohy, R.; Hanna, W.K. A Proposed Method for Multi-Criteria Group Decision Making: An Application to Site Selection. *Appl. Artif. Intell.* **2021**, *35*, 505–519. [CrossRef]
- 7. Jianzhu, S.; Qingshan, Z.; Yinyun, Y. Decision-making for location of manufacturing bases in an uncertain demand situation. *J. Intell. Fuzzy Syst.* **2021**, *41*, 5139–5151. [CrossRef]
- 8. Wong, W.K.; Au, K.F.; Zeng, X.H. Classification decision model for a Hong Kong clothing manufacturing plant locations using an artificial neural network. *Int. J. Adv. Manuf. Technol.* **2006**, *28*, 428–434. [CrossRef]
- 9. Pereira, J.; de Oliveira, E.C.; Gomes, L.F.; Araújo, R.M. Sorting retail locations in a large urban city by using ELECTRE TRI-C and trapezoidal fuzzy numbers. *Soft Comput.* **2019**, 23, 4193–4206. [CrossRef]
- 10. Kuo, R.J.; Chi, S.C.; Kao, S.S. A decision support system for selecting convenience store site through integration of fuzzy AHP and artificial neural network. *Comput. Ind.* 2002, 47, 199–214. [CrossRef]
- Shorabeh, S.N.; Firozjaei, H.K.; Firozjaei, M.K.; Jelokhani-Niaraki, M.; Homaee, M.; Nematollahi, O. The site selection of wind energy power plant using GIS-multi-criteria evaluation from economic perspectives. *Renew. Sustain. Energy Rev.* 2022, 168, 112778. [CrossRef]
- 12. Zolfani, S.H.; Hasheminasab, H.; Torkayesh, A.E.; Zavadskas, E.K.; Derakhti, A. A Literature Review of MADM Applications for Site Selection Problems—One Decade Review from 2011 to 2020. *Int. J. Inf. Technol. Decis. Mak.* **2022**, *21*, 7–57. [CrossRef]
- 13. Ayough, A.; Boshruei, S.; Khorshidvand, B. A new interactive method based on multi-criteria preference degree functions for solar power plant site selection. *Renew. Energy* **2022**, *195*, 1165–1173. [CrossRef]
- 14. Farahani, R.Z.; SteadieSeifi, M.; Asgari, N. Multiple criteria facility site problems: A survey. *Appl. Math. Model.* **2010**, *34*, 1689–1709. [CrossRef]
- 15. Suder, A.; Kahraman, C. Minimizing environmental risks using fuzzy TOPSIS: Site selection for the ITU Faculty of Management. *Hum. Ecol. Risk Assess. Int. J.* 2015, *21*, 1326–1340. [CrossRef]
- 16. Rao, C.; Goh, M.; Zhao, Y.; Zheng, J. Location selection of city logistics centers under sustainability. *Transp. Res. Part D Transp. Environ.* **2015**, *36*, 29–44. [CrossRef]
- 17. Sennaroglu, B.; Celebi, G.V. A military airport site selection by AHP integrated PROMETHEE and VIKOR methods. *Transp. Res. Part D Transp. Environ.* **2018**, *59*, 160–173. [CrossRef]
- 18. Gupta, P.; Mehlawat, M.K.; Grover, N. Intuitionistic fuzzy multi-attribute group decision-making with an application to plant site selection based on a new extended VIKOR method. *Inf. Sci.* **2016**, *370*, 184–203. [CrossRef]
- 19. Kabir, G.; Sumi, R.S. Power substation site selection using fuzzy analytic hierarchy process and PROMETHEE: A case study from Bangladesh. *Energy* **2014**, *72*, 717–730. [CrossRef]
- 20. Samanlioglu, F.; Ayağ, Z. A fuzzy AHP-PROMETHEE II method for evaluation of solar power plant site alternatives in Turkey. J. Intell. Fuzzy Syst. 2017, 33, 859–871. [CrossRef]

- 21. Tian, Z.P.; Wang, J.Q.; Wang, J.; Zhang, H.Y. A multi-phase QFD-based hybrid fuzzy MCDM method for performance evaluation: A case of smart bike-sharing programs in Changsha. *J. Clean. Prod.* **2018**, *171*, 1068–1083. [CrossRef]
- 22. Liu, A.; Wang, R.; Fowler, J.; Ji, X. Improving bicycle sharing operations: A multi-criteria decision-making approach. *J. Clean. Prod.* **2021**, *297*, 126581. [CrossRef]
- 23. Zhou, Z.; Liu, J.; Zeng, H.; Xu, M.; Li, S. Carbon performance evaluation model from the perspective of circular economy—The case of Chinese thermal power enterprise. *Front. Eng. Manag.* **2022**, *9*, 297–311. [CrossRef]
- 24. Karipoğlu, F.; Genç, M.S.; Akarsu, B. GIS-based optimal site selection for the solar-powered hydrogen fuel charge stations. *Fuel* **2022**, *324*, 124626. [CrossRef]
- Chou, C.C. A fuzzy MCDM method for solving marine transshipment container port selection problems. *Appl. Math. Comput.* 2007, 186, 435–444. [CrossRef]
- 26. Chou, S.Y.; Chang, Y.H.; Shen, C.Y. A fuzzy simple additive weighting system under group decision-making for facility site selection with objective/subjective attributes. *Eur. J. Oper. Res.* **2008**, *189*, 132–145. [CrossRef]
- 27. Zolfani, S.H.; Aghdaie, M.H.; Derakhti, A.; Zavadskas, E.K.; Varzandeh, M.H.M. Decision making on business issues with foresight perspective; an application of new hybrid MCDM model in shopping mall locating. *Expert Syst. Appl.* **2013**, *40*, 7111–7121. [CrossRef]
- Latinopoulos, D.; Kechagia, K. A GIS-based multi-criteria evaluation for wind farm site selection. A regional scale application in Greece. *Renew. Energy* 2015, 78, 550–560. [CrossRef]
- 29. Çebi, F.; Otay, İ. Multicriteria and multi-stage facility site selection under interval type-2 fuzzy environment: A case study for a cement factory. *Int. J. Comput. Intell. Syst.* 2015, *8*, 330–344. [CrossRef]
- Wang, C.N.; Nguyen, V.T.; Thai, H.T.N.; Duong, D.H. Multi-criteria decision making (MCDM) methods for solar power plant site selection in Viet Nam. *Energies* 2018, 11, 1504. [CrossRef]
- 31. Jong, F.C.; Ahmed, M.M.; Lau, W.K.; Lee, H.A.D. A new hybrid Artificial Intelligence (AI) approach for hydro energy sites selection and integration. *Heliyon* 2022, *8*, e10638. [CrossRef]
- 32. Deng, X.; Hu, Y.; Deng, Y.; Mahadevan, S. Supplier selection using AHP methodology extended by D numbers. *Expert Syst. Appl.* **2014**, *41*, 156–167. [CrossRef]
- Khan, M.S.A.; Jana, C.; Khan, M.T.; Mahmood, W.; Pal, M.; Mashwani, W.K. Extension of GRA method for multi-attribute group decision making problem under linguistic Pythagorean fuzzy setting with incomplete weight information. *Int. J. Intell. Syst.* 2022, 37, 9726–9749. [CrossRef]
- 34. Mombeni, S.; Darestani, S.A.; Shemami, N.H. Evaluation of the effective factors of unloading and loading goods in ports and the impact on the environment using the MCDM method. *Environ. Sci. Pollut. Res.* **2022**, *online ahead of print*. [CrossRef]
- 35. Xuan, H.A.; Trinh, V.V.; Techato, K.; Phoungthong, K. Use of hybrid MCDM methods for site location of solar-powered hydrogen production plants in Uzbekistan. *Sustain. Energy Technol. Assess.* **2022**, *52*, 101979.
- 36. Vahidnia, M.H.; Vahidi, H.; Hassanabad, M.G.; Shafiei, M. A Spatial Decision Support System Based on a Hybrid AHP and TOPSIS Method for Fire Station Site Selection. *J. Geovis. Spat. Anal.* **2022**, *6*, 30. [CrossRef]
- 37. Rodriguez, V.S.; Mokrova, N. AHP-TOPSIS hybrid decision support system for dam site selection. *Mag. Civ. Eng.* **2022**, *114*, 11405.
- 38. Shao, M.; Zhao, Y.; Sun, J.; Han, Z.; Shao, Z. A decision framework for tidal current power plant site selection based on GIS-MCDM: A case study in China. *Energy* 2023, 262 *Pt B*, 125476. [CrossRef]
- Guleria, A.; Bajaj, R.K. A robust decision-making approach for hydrogen power plant site selection utilizing (R, S)-Norm Pythagorean Fuzzy information measures based on VIKOR and TOPSIS method. *Int. J. Hydrogen Energy* 2020, 45, 18802–18816. [CrossRef]
- 40. Faiza, T.; Muhammad, S. VIKOR method for MCDM based on bipolar fuzzy soft β-covering based bipolar fuzzy rough set model and its application to site selection of solar power plant. *J. Intell. Fuzzy Syst.* **2022**, *42*, 1835–1857.
- 41. Türk, S.; Koç, A.; Şahin, G. Multicriteria of PV solar site selection problem using GIS-intuitionistic fuzzy based approach in Erzurum province/Turkey. *Sci. Rep.* **2021**, *11*, 5034. [CrossRef] [PubMed]
- 42. Dhurkari, R.K. MCDM methods: Practical difficulties and future directions for improvement. *RAIRO-Oper. Res.* 2022, 56, 2221–2233. [CrossRef]
- 43. Lee, S. Determination of priority weights under multi-attribute decision-making situations: AHP versus fuzzy AHP. *J. Constr. Eng. Manag.* **2015**, *141*, 05014015. [CrossRef]
- 44. Chen, X.; Fang, Y.; Chai, J.; Xu, Z. Does intuitionistic fuzzy analytic hierarchy process work better than analytic hierarchy process? *Int. J. Fuzzy Syst.* 2022, 24, 909–924. [CrossRef]
- 45. Tang, K.H.D.; Dawal, S.Z.M.; Olugu, E.U. Integrating fuzzy expert system and scoring system for safety performance evaluation of offshore oil and gas platforms in Malaysia. *J. Loss Prev. Process Ind.* **2018**, *56*, 32–45. [CrossRef]
- 46. Nghiem, T.B.H.; Chu, T.C. Evaluating Lean Facility Layout Designs Using a BWM-Based Fuzzy ELECTRE I Method. *Axioms* 2022, 11, 447. [CrossRef]
- 47. Dymova, L.; Kaczmarek, K.; Sevastjanov, P.; Kulawik, J. A fuzzy multiple criteria decision-making approach with a complete user friendly computer implementation. *Entropy* **2021**, *23*, 203. [CrossRef]

- 48. Wu, J.Z.; Zhang, Q. Multicriteria decision making method based on intuitionistic fuzzy weighted entropy. *Expert Syst. Appl.* **2011**, *38*, 916–922. [CrossRef]
- 49. Li, L.; Zhao, J.; Wang, C.; Yan, C. Comprehensive evaluation of robotic global performance based on modified principal component analysis. *Int. J. Adv. Robot. Syst.* 2020, 17, 1729881419896881. [CrossRef]