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Research Article

Research on the Evaluation Model for Wireless Sensor Network Performance Based on Mixed Multiattribute Decision-Making

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Many application fields initiate using wireless sensor network (WSN), and the evaluation for its performance becomes an important topic, which can help the decision-maker to find the deficiency of the current WSN or seek the best WSN. There exist mixed multiple attributes in the WSN performance evaluation process, for example, some evaluation indicators can be expressed as interval numbers, while others can be expressed as linguistic variables, so it is necessary to explore the evaluation model based on mixed multiattribute decision-making (MADM). Considering the specific evaluation purpose and requirements for different enterprises, this paper puts forward an indicator selection method and a subjective weighting method based on the rough set theory. After that, based on the transformation of mixed attributes into the unified intuitionistic fuzzy numbers (IFNs), an objective weighting method based on intuitionistic fuzzy entropy is proposed. Meanwhile, the combined weights of indicators are obtained by synthesizing the subjective and objective weights. Subsequently, in order to evaluate WSN performance objectively, an integrated comprehensive evaluation framework is proposed, which includes single evaluation, compatibility test, combination evaluation, and consistency test. The paper gives specific models and calculation steps in detail. Finally, it provides a case study to explain the application of the proposed indicator selection method and the evaluation models, which provide new ideas and references for WSN performance evaluation.

1. Introduction

WSN is a combination of multiple sensor nodes, which play a role in real-time sensing, collecting, processing, and transmitting the sensing object information. In recent years, WSN has become more and more popular in many fields, such as environmental monitoring, Internet of Things, factory maintenance, and target tracking on battlefields. In particular, enterprise production and people's life more and more rely on WSN, and how to evaluate the performance of WSN becomes more and more vital. Scientific evaluation can help decision-makers objectively compare the performance of different WSNs, so as to get the objective comparison result, improve the performance of existing WSN, or provide decision support for the selection of the best WSN. Many scholars have focused on the performance evaluation of WSN. According to the evaluation object, it mainly includes link quality [1–3], protocol performance [4–7], quality of service (QoS) [8–11], reliability [12–15], robustness [16–18], and overall performance [19–23]. Gomes et al. [1] used the received signal strength indication and data packet information as indicators to test the link quality of industrial WSN. Jayasri and Hemalatha [2] put forward the link quality parameters and used Kalman filter method to evaluate the link quality. Shu et al. [3] established a link quality estimation model in terms of a support vector machine with a decision tree. Chen et al. [4] evaluated protocol performance according to coverage awareness and energy saving. Souil et al. [5] analyzed the performance of media access control (MAC) protocol using transmission probability and data delivery ratio. Mokdad et al. [6] used loss probabilities, average delay, and average delivery ratio as performance indicators to evaluate the protocol. Ketshabetswe et al. [7] compared the property of different routing protocols based on latency, success rate, energy consumption, and energy efficiency. Arora et al. [8] used throughput, end-to-end delay, network load, and other indicators to evaluate the QoS of WSN. Long et al. [9] constructed a network layer QoS

evaluation indicator system including throughput, the success rate of communication, packet loss rate, and energy efficiency. Wu et al. [10] proposed a QoS evaluation model in the basis of ideal points of vague sets. Kumar et al. [11] reviewed the machine learning techniques in QoS evaluation of WSN, including artificial neural network and reinforcement learning. He et al. [12] evaluated WSN reliability in terms of hierarchical trust rules, which combined fault evaluation with security evaluation. Zhu et al. [13] established the transmission reliability evaluation models for WSNs. Sun and Willmann [14] proposed a dependability evaluation method of industrial WSN based on deep learning. Yue and He [15] summarized the research progress of mobile WSN reliability and qualitatively analyzed different reliability schemes from packet loss rate, throughput, connectivity, and other aspects. Hu and Li [16] proposed the measurement metrics of WSN robustness, including betweenness, node degree, and connectivity coverage. Acharya and Tripathy [17] proposed four WSN cluster deployment models and compared their robustness from the first node dies, network lifetime, energy cost, and other indicators. Wang et al. [18] proposed robustness performance indicators such as power consumption, cost, and message delay and established an evaluation model based on the extension cloud theory. Jiang et al. [19] used gain-cost to represent the performance of the entire network and combined the three evaluation indicators of network efficiency, network reliability, and network connection energy cost into a function of net revenue. Zhou and Li [20] selected time delay, packet loss rate, and throughout as evaluation indicators and adopted the linear weighting method for comprehensive evaluation. Anwar et al. [21] compared trust-based security WSN and key-based security WSN from two aspects of time delay and throughput. Li et al. [22] proposed a hierarchy model from three aspects of availability, dependability, and capability and established a weighted comprehensive evaluation model for WSN performance. Luan et al. [23] summarized the performance evaluation indicators of WSN in the network layer, survivability, monitoring performance, and positioning technology and introduced a linear weighted comprehensive evaluation method. Literature review shows that the performance evaluation of WSN is actually a comprehensive process of multiple indicators. Among the evaluation methods in the existing literature, the performance indicators of WSN are mostly expressed by precise real numbers. In fact, due to the passage of time and the instability of the external environment, the values of indicators such as time delay and packet loss rate are often uncertain. In addition, the values of qualitative indicators can be expressed as linguistic variables. Therefore, based on the mixed MADM method, the establishment of a comprehensive evaluation model of WSN performance is more realistic, and the conclusion will be more scientific.

There are many ways to express the attributes of evaluation objects, which can be divided into deterministic attributes and uncertain attributes [24]. Due to the uncertainty and variability of the environment, the research on the expression and decision-making of uncertain attributes is increasingly in-depth. Zadeh [25] first proposed the concept of the fuzzy set (FS). On the basis of FS, Atanassov [26] and Torra and Narukawa [27], respectively, introduced the intuitionistic fuzzy set (IFS) and hesitant fuzzy set (HFS) for further describing the uncertain characteristics. To associate the occurring probability of hesitant fuzzy numbers, Xu and Zhou [28] presented the probabilistic HFS. Zhu et al. [29] introduced the dual HFS as an extension of FS. Yager [30] developed the Pythagorean fuzzy set (PyFS). Cuong [31] and Smarandache [32], respectively, proposed the picture fuzzy set (PFS) and neutrosophic set as the general forms of FS and IFS. Considering that fuzzy language terms were often used for qualitative description, Zadeh [33] proposed the linguistic variable (LV) characterized by a fuzzy compatibility function. Wang and Li [34] and Rodriguez et al. [35], respectively, introduced the intuitionistic LV and the hesitant fuzzy LV. Xu [36] proposed the uncertain LV with the lower and upper limits. For comparing multiple evaluation objects, a lot of MADM methods have been developed to accommodate different attribute types. Xu and Zhao [37] reviewed the aggregation operators of IFS and proposed that some operators have ideal properties. Beliakov et al. [38] introduced the definition of the generalized aggregation of IFS, which can deal with the failure caused by the extreme value. Liu and Jin [39] developed a hybrid geometric operator of the intuitionistic uncertain LV. Besides the aggregation operator methods, some traditional methods in MADM are widely used, including distance measure [37, 39], TOPSIS (technique for order preference by similarity to ideal solution) [40], GRA (grey relational analysis) [41, 42], VIKOR (Vlse Kriterijumska Optimizacija I Kompromisno Resenje) [43–45], and ER (evidence reasoning) methods [45, 46]. For the mixed MADM problem, scholars mainly put forward the distance-based methods [47–49] and the transformation technique-based methods [46, 50–55]. Lourenzutti and Krohling [48] and Pan and Geng [49], respectively, proposed a group modular random TOPSIS method and a modular random VIKOR method, which can break heterogeneous information into independent attribute modules and process information in a straight forward way without unifying. Wang and Li [50] determined the ideal alternatives and developed an interactive MADM method. Herrera et al. [51] and Liu [52] transformed the heterogeneous information into the 2-tuple LV and ranked the alternatives by dominance degree and 2-tuple linguistic weighting arithmetic average values, respectively. Bao et al. [46] aggregated the heterogeneous information into IFNs and applied integrating prospect theory and ER to rank the alternatives. Xu et al. [53] proposed an approach that aggregates the heterogeneous information into IFNs by group evaluation in rating system and TOPSIS and applied intuitionistic weighted arithmetic mean operator for ranking the alternatives. Wan et al. [54, 55] proposed an aggregation method for fusing heterogeneous information into interval-valued IFNs and applied a weighted averaging operator for ranking the alternatives. Because the transformation technique-based methods can avoid information loss to a certain extent, the research on them in mixed MADM is more extensive in recent years.

To sum up, scholars have established various WSN performance evaluation indicator systems and proposed various comprehensive evaluation models. However, the current

research needs to be deepened in the following two aspects: (1) Different evaluation subjects have different goals and requirements, so how to select evaluation indicators according to their actual situation? (2) There are both deterministic attributes and uncertain attributes in the evaluation indicator system. How to establish a more scientific comprehensive evaluation model based on the mixed MADM method? This study mainly focuses on the above two aspects, and its contributions are as follows: (1) A rough set method for WSN performance evaluation indicator selection is proposed, which can make full use of the experience of the field experts and provide relatively complete indicators that meet the needs of decision-makers. (2) An indicator weighting method based on subjective and objective synthesis is proposed, in which the subjective and objective weights of each indicator are obtained by the rough set method and by entropy technique, respectively. (3) An evaluation model based on intuitionistic fuzzy MADM is proposed, which integrates single evaluation, compatibility test, combination evaluation, and consistency test.

This article is organized as follows: Section 2 presents the indicator selection method on the basis of the rough set. Section 3 presents the indicator weighting method based on rough set and intuitionistic fuzzy entropy. Section 4 presents the evaluation model based on intuitionistic fuzzy MADM. Section 5 illustrates an example of the evaluation and selection of the WSN partner to demonstrate how to apply the proposed model. Section 6 concludes the study.

2. Indicator Selection Based on Rough Set

Due to the different evaluation purposes and requirements of WSN performance, it is difficult to establish a consistent indicator system. We design an indicator selection method based on the rough set theory to solve this problem [56, 57]. It is assumed that a comprehensive evaluation indicator system containing two levels of indicators has been preliminarily established by referring to relevant literature. The evaluation organizers investigate h experts with rich practical experience in the WSN field and invite each expert to judge the importance of t primary indicators and the corresponding secondary indicators according to the Likert's five-level scale method. The numbers from 1 to 5 represent unimportant, general, important, very important, and especially important, respectively. With each primary indicator as the decision attribute and all the corresponding secondary indicators as the condition attributes, we can get t decision tables. It shows the decision table form in Table 1, where $x_i^{(j)}$ and d_i are Likert values given by the ith expert for the importance of C_j and D relative to WSN performance evaluation.

The steps of indicator selection based on a rough set are as follows:

Step 1. According to the decision attribute D, divide the argument domains $U = \{1, 2, \cdots, h\}$ into q equivalent classes: $U/D = \{H_1, H_2, \cdots, H_q\}$.

Table 1: Decision table of a primary indicator with the corresponding secondary indicators.

Expert serial number	Condition attributes C_1	C_2	…	C_s	Decision attribute D
1	$x_1^{(1)}$	$x_2^{(1)}$	…	$x_s^{(1)}$	d_1
2	$x_1^{(2)}$	$x_2^{(2)}$	…	$x_s^{(2)}$	d_2
…	…	…	…	…	…
h	$x_1^{(h)}$	$x_2^{(h)}$	…	$x_s^{(h)}$	d_h

Step 2. Calculate the lower approximation of the kth equivalence class H_k regarding the conditional attribute set $C = \{C_1, C_2, \cdots, C_s\}$ as follows:

$$\underline{C}H_k = \bigcup \left\{ Y \in \frac{U}{C} \right\}, k = 1, 2, \cdots, q. \tag{1}$$

The C positive domain of D is as follows:

$$\mathrm{pos}(C, D) = \bigcup_{k=1}^{q} \underline{C}H_k. \tag{2}$$

Step 3. Remove the attribute C_j from C, $j = 1, 2, \cdots s$ and calculate $\mathrm{pos}(C - C_j, D)$. If $\mathrm{pos}(C - C_j, D) = \mathrm{pos}(C, D))$, it means that C_j is a redundant attribute and can be deleted from C. Then, we can get the reduced conditional attribute set.

Step 4. According to step 2 and step 3, continue to test whether there are redundant attributes in the reduced condition attribute set until all of the attributes are nonredundant. Then, we can get the reduced secondary indicator set C^r.

3. Indicator Weighting Based on Rough Set and Intuitionistic Fuzzy Entropy

The indicator weight has an important influence on the results of WSN performance evaluation. The subjective weight of the indicator is calculated by using the concept of relativity of rough set, so as to reflect the experts' cognition of the importance of each indicator. At the same time, the objective weight can be obtained by the intuitionistic fuzzy entropy, which can reflect the difference between the indicator values in the actual evaluation.

3.1. Indicator Weighting Based on Rough Set. Based on the reduced secondary indicators C^r, we calculate the dependence of D on C^r as follows: $\gamma(C^r, D) = |\mathrm{pos}(C^r, D)|/|U|$, where $|\bullet|$ represents the cardinality of the set. Then, we calculate the dependence of D on the condition attribute C_j in C^r: $\sigma_{CD}(C_j) = \gamma(C^r, D) - \gamma(C^r - C_j, D)$. By standardizing $\sigma_{CD}(C_j)$ as follows:

$$w_j = \frac{\sigma_{CD}(C_j)}{\sum_{C_j \in C^r} \sigma_{CD}(C_j)}, \tag{3}$$

we can get the subjective weight of each secondary indicator relative to the primary indicator.

For a small number of primary indicators, experts can jointly determine weights based on their experience. By multiplying the weight of the secondary indicator by its corresponding weight of the primary indicator, we can obtain the composite weight of each secondary indicator. Suppose there are n secondary indicators after reduction, and their subjective weights are denoted as $\eta_j, j = 1, 2, \cdots n$.

3.2. Indicator Weighting Based on Intuitionistic Fuzzy Entropy. Because IFS take the information of membership degree, nonmembership degree, and hesitation degree into consideration at the same time, it can more accurately reflect the objective reality, and it is more reasonable for decision-makers to understand and apply. Therefore, different types of evaluation information can be uniformly transformed into IFNs, and on this basis, the weight of each attribute can be determined and the MADM can be made. references [46, 53] provided different methods to aggregate heterogeneous information into IFNs. The former is applicable to the case containing both qualitative and quantitative attributes, and the values of qualitative attributes are jointly given by group members. The latter is applicable to the case that all the attributes are qualitative, and multiple decision-makers, respectively, give the value of some attribute in the same rating system. Here, we suppose that all the attribute values of each alternative are known and refer to the former method to aggregate precise numbers, interval numbers, and linguistic variables into IFNs. Since the normalization method in [46] may produce the extreme (1, 0), making the comparison of different alternatives less objective, we suggest replacing the normalization method with vector normalization. For the triangular fuzzy numbers (TFNs) or trapezoidal fuzzy numbers (TrFNs), we can extract their cut sets and convert them to interval numbers [58]. The values of n secondary indicators of m WSNs comprise the evaluation matrix $[x_{ij}]_{m\times n}$.

Case 1. If the value of the jth indicator of each WSN is a positive precise real number, $x_{ij} > 0, i = 1, 2, \cdots m$, we can use the formula (4) to get dimensionless value y_{ij} and then convert y_{ij} to the intuitionistic fuzzy number $z_{ij} = (u_{ij}, v_{ij}) = (y_{ij}, 1 - y_{ij})$.

$$y_{ij} = \begin{cases} \dfrac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}}, & c_j \in C_{\text{benefit}}, \\ \dfrac{1/x_{ij}}{\sqrt{\sum_{i=1}^{m} \left(1/x_{ij}\right)^{2}}}, & c_j \in C_{\text{cost}}, \end{cases} \tag{4}$$

where C_{benefit} and C_{cost} represent the benefit attribute set and the cost attribute set, respectively.

Case 2. If x_{ij} is an interval number $[x_{ij}{}^{L}, x_{ij}{}^{R}]$, $0 < x_{ij}{}^{L} \le x_{ij}{}^{R}$, $i = 1, 2, \cdots m$, we can convert it to a dimensionless interval number $[y_{ij}{}^{L}, y_{ij}{}^{R}]$ by using the formula (5).

$$\begin{cases} y_{ij}^{L} = \dfrac{x_{ij}^{L}}{\sqrt{\sum_{i=1}^{m}\left(x_{ij}^{R}\right)^{2}}}, y_{ij}^{R} = \begin{cases} \dfrac{x_{ij}^{R}}{\sqrt{\sum_{i=1}^{m}\left(x_{ij}^{R}\right)^{2}}}, \dfrac{x_{ij}^{R}}{\sqrt{\sum_{i=1}^{m}\left(x_{ij}^{L}\right)^{2}}} \le 1, \\ \dfrac{x_{ij}^{R}}{\sqrt{\sum_{i=1}^{m}\left(x_{ij}^{R}\right)^{2}}}, \dfrac{x_{ij}^{R}}{\sqrt{\sum_{i=1}^{m}\left(x_{ij}^{L}\right)^{2}}} > 1, \end{cases} & , c_j \in C_{\text{benefit}}, \\ y_{ij}^{L} = \dfrac{1/x_{ij}^{R}}{\sqrt{\sum_{i=1}^{m}\left(1/x_{ij}^{L}\right)^{2}}}, y_{ij}^{R} = \begin{cases} \dfrac{1/x_{ij}^{L}}{\sqrt{\sum_{i=1}^{m}\left(1/x_{ij}^{R}\right)^{2}}}, \dfrac{1/x_{ij}^{L}}{\sqrt{\sum_{i=1}^{m}\left(1/x_{ij}^{R}\right)^{2}}} \le 1, \\ \dfrac{1/x_{ij}^{L}}{\sqrt{\sum_{i=1}^{m}\left(1/x_{ij}^{L}\right)^{2}}}, \dfrac{1/x_{ij}^{L}}{\sqrt{\sum_{i=1}^{m}\left(1/x_{ij}^{R}\right)^{2}}} > 1. \end{cases} & , c_j \in C_{\text{cost}}. \end{cases} \tag{5}$$

The corresponding intuitionistic fuzzy number is $(y_{ij}^{L}, 1 - y_{ij}^{R})$. Among them, the precise real number of x_{ij} can be first converted to an interval number $[x_{ij}, x_{ij}]$.

Case 3. If x_{ij} is a triangular fuzzy number $(x_{ij}^{L}, x_{ij}^{M}, x_{ij}^{R})$ or a trapezoidal fuzzy number $(x_{ij}^{L}, x_{ij}^{M}, x_{ij}^{G}, x_{ij}^{R})$, we can convert it to an interval number $[x_{ij}^{L} + (x_{ij}^{M} - x_{ij}^{L})\alpha, x_{ij}^{R} - (x_{ij}^{R} - x_{ij}^{M})\alpha]$ or $[x_{ij}^{L} + (x_{ij}^{M} - x_{ij}^{L})\alpha, x_{ij}^{R} - (x_{ij}^{R} - x_{ij}^{G})\alpha]$ by extracting its α-cut set and then convert the interval number to the intuitionistic fuzzy number according to the Case 2.

Case 4. If x_{ij} is an uncertain linguistic variable $[x_{ij}^{LL}, x_{ij}^{LR}]$. $x_{ij}^{LL}, x_{ij}^{LR} \in L = \{l_0, l_1, \cdots, l_6\}$, $x_{ij}^{LL} \prec x_{ij}^{LR}$, we can quantify it to an interval number $[x_{ij}^{L}, x_{ij}^{R}]$ by the two-level proportion method (see Table 2) and convert it to the intuitionistic fuzzy number which is $(y_{ij}^{L}, 1 - y_{ij}^{R})$ according to the Case 2. Among them, a certain linguistic variable can be first converted to an uncertain language variable $[x_{ij}, x_{ij}]$.

Entropy can reflect the degree of numerical dispersion, and the entropy method is often used for objective weighting of indicators. There are many discussions on intuitionistic fuzzy entropy [47, 59, 60]. According to the scientific axiomatic definition in reference [59], we conduct traversal simulation of various measurement formulas on the set of an intuitionistic fuzzy number $\{(u, v) \mid u \in [0, 1], v \in [0, 1 - v]\}$ and choose the formula in reference [47]. Based on the matrix $Z = [z_{ij}]_{m\times n}$, the intuitionistic fuzzy entropy of the j th indicator is as follows:

$$E_j = \frac{1}{m}\sum_{i=1}^{m} \frac{1 - s_{ij}{}^{2} + 2\left(1 - \pi_{ij}\right)}{2 - s_{ij}{}^{2} + \left(1 - \pi_{ij}\right)}, j = 1, 2, \cdots, n, \tag{6}$$

where s_{ij} is the score of z_{ij}: $s_{ij} = u_{ij} - v_{ij}$ and π_{ij} is the accuracy of z_{ij}: $\pi_{ij} = u_{ij} + v_{ij}$.

The objective weight of the jth indicator is as follows:

$$\tau_j = \frac{1 - E_j}{\sum_{j=1}^{n}\left(1 - E_j\right)}, j = 1, 2, \cdots, n. \tag{7}$$

Table 2: The corresponding of two-level proportion method.

Cost attribute	Highest	Very high	High	Average	Low	Very low	Lowest
Benefit attribute	Lowest	Very low	Low	Average	High	Very high	Highest
Quantitative value	0	1	3	5	7	9	10
Standard value	0	0.0286	0.0857	0.1429	0.2000	0.2571	0.2857

Let the weight of subjective weights be α and that of objective weights 1-α, and we can get the comprehensive weight of each indicator: $w_j = \alpha\eta_j + (1-\alpha)\tau_j, j = 1, 2, \cdots, n$.

4. Evaluation Model Based on Intuitionistic Fuzzy MADM

When all the values of attributes are uniformly transformed into IFNs, WSN performance evaluation becomes an intuitionistic fuzzy MADM problem. As mentioned in the literature review, there are many intuitionistic fuzzy MADM methods. For the intuitionistic fuzzy MADM problems with known weights, the researched models mainly include aggregation operator, TOPSIS, VIKOR, GRA, and ER models. Different models have their own based-techniques and basic principles, which are summarized in Table 3. It is difficult to determine which model is most suitable for WSN performance evaluation. Each of these models is theoretically applicable. In order to fully utilize the results of various models, we put forward a combination evaluation framework that includes a single evaluation, Kendall compatibility test, combination evaluation, and Spearman consistency test.

4.1. Single Evaluation Models. Combined with the research progress of aggregation operator, TOPSIS, VIKOR, GRA, and ER models, we provide the following single performance evaluation models for WSN.

4.1.1. Aggregation Operator Model. There are a variety of forms of aggregation operators [37]. Because the HWA (hybrid weighted averaging) operator considers both the importance and the position of attributes and has such ideal properties as idempotency, boundedness, and monotony, we select HWA operator for WSN performance evaluation. The calculation steps are as follows:

Step 1. Calculate the weighted matrix: $Z' = [(z'_{ij})]_{m\times n}$, where

$$z'_{ij} = w_j(u_{ij}, v_{ij}) = \left(1 - (1-u_{ij})^{w_j}, v_{ij}^{w_j}\right) \tag{8}$$

Step 2. Calculate the score and accuracy of z'_{ij}. In terms of the sorting rule of IFNs: (1) the higher score, the greater value; (2) when the scores are the same, the higher accuracy, the greater value, and we reorder the values of n indicators of each WSN from large to small. Let $z_{i\sigma(j)}'$ be the jth intuitionistic fuzzy number, $j = 1, 2, \cdots, n$, and we can get the corresponding value before weighted $z_{i\sigma(j)}$ and the indicator weight $w_{i\sigma(j)}$.

Step 3. Calculate the position weight vector by the normal distribution method. Let ω_j be the weight of the jth position; then, the comprehensive value of the ith WSN is as follows:

$$f_i = \left(1 - \prod_{j=1}^{n}\left(1-u_{i\sigma(j)}\right)^{w_j w_{i\sigma(j)} / \sum_{j=1}^{n} w_j w_{i\sigma(j)}}, \prod_{j=1}^{n}\left(v_{i\sigma(j)}\right)^{w_j w_{i\sigma(j)} / \sum_{j=1}^{n} w_j w_{i\sigma(j)}}\right), i = 1, 2, \cdots, m. \tag{9}$$

Step 4. Calculate the score and accuracy of $f_i, i = 1, 2, \cdots, m$ and sort WSNs according to the sorting rule of IFNs.

4.1.2. TOPSIS Model. The basic principle of the TOPSIS model is to compare each object by its relative proximity to the ideal points. The calculation steps are as follows:

Step 1. Determine the positive and negative ideal points of evaluation matrix Z:

$$z^+ = [z_1^+, z_2^+, \cdots, z_n^+], z^- = [z_1^-, z_2^-, \cdots, z_n^-], \tag{10}$$

where $z_j^+ = (\max_i u_{ij}, \min_i v_{ij}\}$ and $z_j^- = (\min_i u_{ij}, \max_i v_{ij}\}$.

Step 2. Calculate the distance between the ith object and the positive and negative ideal points:

$$d_i^+ = \sum_{j=1}^{n} w_j d\left(z_{ij}, z_j^+\right), d_i^- = \sum_{j=1}^{n} w_j d\left(z_{ij}, z_j^-\right), i = 1, 2, \cdots, m. \tag{11}$$

Because the distance measure in reference [47] can consider the characteristics of fluctuation and nonconcreteness of intuitionistic fuzzy information, we apply it to calculate the distance between two IFNs $z_1 = (u_1, v_1)$ and $z_2 = (u_2, v_2)$, and the formula is as follows:

$$\begin{aligned} d(z_1, z_2) = {} & \frac{1}{6}[|u_1 - u_2| + |v_1 - v_2| + |s_1 - s_2| + (1-\pi_1) \\ & + (1-\pi_2)] + \frac{1}{3}\max\left(|u_1 - u_2|, |v_1 - v_2|, \frac{|\pi_1 - \pi_2|}{2}\right). \end{aligned} \tag{12}$$

In the formula (12), s_k and π_k are the score and accuracy of z_k, respectively, $k = 1, 2$.

Step 3. Calculate the proximity of the ith WSN:

$$c_i = \frac{d_i^-}{d_i^- + d_i^+}, i = 1, 2, \cdots, m. \tag{13}$$

Table 3: Different intuitionistic fuzzy MADM models and their principles.

Model	Based-techniques	Basic principle
Aggregation operator	Weighted integration	Intuitionistic fuzzy number after weighted aggregation
TOPSIS	Distance measure	The relative proximity from the ideal points
VIKOR	Distance measure	The trade-off between group utility and individual regret
GRA	Relational coefficient	The grey relation degree with the reference sequence
ER	Evidential reasoning algorithms, distance measure	The belief degree relative to the ideal points

Sort all the WSNs according to their proximities from large to small.

4.1.3. VIKOR Model. VIKOR model takes both group utility and individual regret into account, and it can reflect the preference of decision-makers by the trade-off coefficient. Firstly, calculate the group utility value P_i and the individual regret value N_i of the ith WSN:

$$P_i = \sum_{j=1}^{n} \frac{w_j d\left(z_{ij}, z_j^+\right)}{d\left(z_j^-, z_j^+\right)}, i = 1, 2, \cdots, m,$$
$$N_i = \max_j \frac{w_j d\left(z_{ij}, z_j^+\right)}{d\left(z_j^-, z_j^+\right)}, i = 1, 2, \cdots, m. \tag{14}$$

Secondly, calculate the benefit ratio value Q_i:

$$Q_i = \frac{\gamma\left(P_i - \min_k P_k\right)}{\max_k P_k - \min_k P_k} + \frac{(1-\gamma)\left(N_i - \min_k N_k\right)}{\max_k N_k - \min_k N_k}, i = 1, 2, \cdots, m, \tag{15}$$

where γ is the trade-off coefficient between the group utility and individual regret, $0 \le \gamma \le 1$.

Finally, sort all the WSNs according to their benefit ratio values from small to large.

4.1.4. GRA Model. The principle of GRA is to evaluate each object according to its relation degree with the reference sequence (usually positive ideal point). Firstly, calculate the relation coefficient between the jth indicator of the ith WSN and the positive ideal point:

$$\xi_{ij} = \frac{\min_i \min_j d\left(z_{ij}, z_j^+\right) + \rho \max_i \max_j d\left(z_{ij}, z_j^+\right)}{d\left(z_{ij}, z_j^+\right) + \rho \max_i \max_j d\left(z_{ij}, z_j^+\right)}, i = 1, 2, \cdots, m; j = 1, 2, \cdots, n, \tag{16}$$

where ρ is the distinguishing coefficient, $\rho \in [0, 1]$.

Secondly, calculate the relation degree of the ith WSN:

$$\xi_i = \sum_{j=1}^{n} w_j \xi_{ij}, i = 1, 2, \cdots, m. \tag{17}$$

Finally, sort all the WSNs according to their relation degrees from large to small.

4.1.5. ER Model. Each indicator of the evaluation object in the ER model is regarded as proof. Based on the identification framework composed of multiple evaluation grades, we can evaluate each proof and get the belief degree that it belongs to each grade. By combining the weight of each indicator, we can use the evidence of reasoning algorithm to get the belief degree of the evaluation object. In this paper, we use the IDS software for the evidence of reasoning of WSN performance [61], and the steps are as follows:

Step 1. Build an indicator hierarchy comprising a top attribute and n bottom attributes. The top attribute has the best and the worst grade, and the utility values are 1 and 0, respectively. The bottom attributes also have the best and the worst grade, and the belief degree vectors of them for the combination (best, worst) are (1, 0) and (0, 1), respectively. Input the weights of n bottom attributes into the IDS software.

Step 2. Insert m alternatives and input the belief degree that the jth indicator of the ith alternative belongs to the best and worst grades, that is, the value expressed in the form of an intuitionistic fuzzy number (u_{ij}, v_{ij}).

Step 3. Evaluate the ith alternative and get the belief degree vector of the top attribute for the combination (best, worst), namely, the intuitionistic fuzzy number $e_i = (u_i, v_i)$, $i = 1, 2, \cdots m$.

Step 4. Calculate the score and accuracy of e_i and sort all the WSNs according to the sorting rule of an intuitionistic fuzzy number.

4.2. Kendall Compatibility Test. Since the evaluation results of the above single models may differ greatly, we need to obtain less divergent evaluation results through compatibility test, so as to conduct further combination evaluation [62]. Let r_{ik} be the rank of the ith WSN in the kth single model, $i = 1, 2, \cdots, n$; $k = 1, 2, \cdots, g$. When $n \le 7$, we can calculate Kendall's coefficient of concordance as follows:

$$s = \sum_{i=1}^{n} {r_i}^2 - \frac{1}{n}\left(\sum_{i=1}^{n} r_i\right)^2 = \sum_{i=1}^{n}\left(\sum_{k=1}^{g} r_{ik}\right)^2 - \frac{1}{n}\left(\sum_{i=1}^{n}\sum_{k=1}^{g} r_{ik}\right)^2. \tag{18}$$

Given the significance level α, if the value s is no less than the critical value $s_\alpha(g, n)$, then the g models are compatible.

When $n > 7$, we calculate the statistical indicator: $\chi^2 = g(n-1)W$, where

$$W = \frac{12\sum_{i=1}^{n} r_i^2}{g^2 n(n^2-1)} - \frac{3(n+1)}{n-1}. \tag{19}$$

Given the significance level α, if the value χ^2 is no less than the critical value ${\chi^2}_\alpha(n-1)$, then the g models are compatible.

For the case of incompatibility, we can calculate the statistical indicator of the remaining models by eliminating a single model and obtain the set of compatible models with the largest statistical value.

4.3. Combination Evaluation Models. The evaluation values of each WSN in the above single models are all in the range [-1, 1], and their meanings are clear. In order to fully utilize of the evaluation information, we further carry out the combination evaluation according to the numerical value rather than ranking. To eliminate the influence of actual value range difference between models and keep the correlation of the previous results unchanged, we firstly apply the extremum transformational method to convert the original results into the range [0, 1]. Among them, the benefit ratio value in the VIKOR model is converted according to the conversion method of the cost indicator, and the results of the other four models are converted according to the conversion method of the benefit indicator. Let t_{ik} be the result from the ith WSN in the kth compatible model after the extremum transformation, $i = 1, 2, \cdots, m$, $k = 1, 2, \cdots, g$. The widely used combination evaluation models based on the numerical value mainly include averaging, principal component analysis (PCA), MSE- (mean square error-) based weighted, optimization, drift, and cooperative game models [63, 64]. Since the PCA model requires a large number of samples, we apply the other five models for combination evaluation.

4.3.1. Averaging Model. All the single evaluation models have the same status in this combination model, and the average value of the results in g compatible models for each WSN is its combination evaluation result.

4.3.2. MSE-Based Weighted Model. This model is an objective weighted method. By calculating the MSE of the kth compatible model and taking its proportion to the MSEs' sum of all the g models as the weight w_k, we can calculate the combination evaluation result of each WSN as follows:

$$t_i = \sum_{k=1}^{g} w_k t_{ik}, i = 1, 2, \cdots, m. \tag{20}$$

4.3.3. Optimization Model. The objective function is to minimize the sum of the error squares between the weighted combination results and the single evaluation results of all WSNs. We can get the optimal weights of all the compatible models by solving the optimization model and can calculate the combination evaluation result by substituting them into formula (20).

4.3.4. Drift Model. Assuming there exists an objective model, the weight of each model can be calculated based on the drift of its result relative to the result of the objective model. The further the drift, the greater the weight. In this paper, we assume that the averaging model, MSE-weighted model, or optimization model is the objective model and record its evaluation result as the reference $r = [r_1, r_2, \cdots, r_m]$. Calculate the correlation coefficient c_k between the result of the kth single evaluation model and the reference [65], then the drift is $p_k = 1 - c_k$, and the weight is as follows:

$$w_k = \frac{\max_l p_l + \min_l p_l - p_k}{\sum_{k=1}^{g}\left(\max_l p_l + \min_l p_l - p_k\right)}, k = 1, 2, \cdots, g. \tag{21}$$

Substitute the weights of all the single evaluation models into the formula (20), and we can get the combination evaluation result.

4.3.5. Cooperative Game Model. Assuming there exists an objective model, we calculate the average absolute error between the result of the kth single evaluation model and that of the objective model as the characteristic function of the alliance $\{k\}$:

$$v(\{k\}) = \frac{\sum_{i=1}^{m}|t_{ik} - r_i|}{m}, k = 1, 2, \cdots, g. \tag{22}$$

Similarly, we can calculate the characteristic functions of the $2^g - 2$ alliances. Let $v(S) - v(S \setminus \{k\})$ be the contribution of the kth model to alliance S, and then, we can get the Shapley value ϕ_k of the kth model as its average contribution to the whole alliance $\Omega = \{1, 2, \cdots, g\}$:

$$\phi_k = \sum_{S \subset \Omega} \frac{(g - |S|)!(|S| - 1)!}{g!}[v(S) - v(S\{k\})], k = 1, 2, \cdots, g. \tag{23}$$

The weight of the kth model is as follows:

$$w_k = \frac{1}{g-1} \bullet \frac{v(\Omega) - \phi_k}{v(\Omega)}, k = 1, 2, \cdots, g. \tag{24}$$

Substitute the weights of all the single evaluation models into the formula (20), and then, we can get the combination evaluation result.

4.4. Spearman Consistency Test. The method of Spearman rank correlation coefficient can be used to test the consistency between each combination evaluation model and all the compatible model set [63, 64]. The Spearman rank correlation coefficient between the lth combination model and the

kth single evaluation model is as follows:

$$\rho_{lk} = 1 - \frac{6\sum_{i=1}^{n}(p_{il} - p_{ik})^2}{n(n^2 - 1)}, \tag{25}$$

where p_{il} and p_{ik} are the ranks of the ith WSN in the lth combination evaluation model and the kth single evaluation model, respectively, $i = 1, 2, \cdots, n$; $l = 1, 2, \cdots, 9$; $k = 1, 2, \cdots, g$.

When $n < 10$, we calculate the average correlation coefficient as follows:

$$\rho_l = \frac{1}{g}\sum_{k=1}^{g}\rho_{lk}, l = 1, 2, \cdots, 9. \tag{26}$$

Then, we output the ranking result in the combination model with the maximum average correlation coefficient as the ultimate evaluation result.

When $n \geq 10$, we can calculate the statistical indicator as follows:

$$t_l = \rho_l\sqrt{\frac{n-2}{1-\rho_l^2}}, l = 1, 2, \cdots, 9. \tag{27}$$

Given the significance level α, if the value t_l is no less than the critical value $t_\alpha(n-2)$, it means that the lth combination evaluation model is consistent with the compatible model set. Then, we output the ranking result of the combination model with the largest statistical value and passed the consistency test as the final evaluation result.

5. A Case Study

The decision-makers of company H, a manufacturer of cold chain products, plan to choose the best WSN partner for the Internet of Things from five WSNs: $A_1, A_2, \cdots, A_5$. The preliminary evaluation indicator system is shown in Figure 1.

Considering the possibility of redundancy between indicators, we use the proposed rough set method to select indicators. Taking the network layer QoS as an example, we get the decision table by consulting ten experts in Table 4. For example, the first expert thinks that the packet loss rate is especially important for the network layer QoS, and network layer QoS is important for the WSN performance evaluation, so the Likert value for the importance of the packet loss rate is 5, and that of the network layer QoS is 3. Following the reduction steps, we get five reduction sets of conditional attributes that include {energy consumption balance, time delay}, {energy consumption balance, time delay jitter}, {packet loss rate, energy consumption balance, time delay jitter}, {energy efficiency, energy consumption balance, time delay jitter}, and {packet loss rate, throughout, energy efficiency, time delay}. Through further consultation with experts, we select the four elements in the fifth reduction set as the secondary indicators.

Similarly, we get the secondary indicators of reliability including security, survivability, and anti-interference capability and those of monitoring performance including network coverage, self-organizing ability, and sensor node capability. According to formula (3), we calculate the weight of each secondary indicator relative to the primary indicator. The experts consider that each primary indicator has the same weight 1/3; then, we can get the weight of each indicator for WSN performance evaluation in Table 5.

Through expert interviews and data monitoring, we get the original evaluation data of five alternative WSN partners in Table 6. The indicators C_1, C_2, C_3, and C_4 are expressed as interval numbers, C_8 is expressed as a precise real number, and the other five indicators are expressed linguistic variables from the seven-level linguistic term set {highest, very high, high, average, low, very low, lowest}.

After vector normalization of the above evaluation matrix elements and the unified conversion to IFNs, we get the intuitionistic fuzzy decision-making matrix as follows:

$$Z' = \begin{bmatrix} (0.2911,0.5602) & (0.2815,0.3716) & (0.2657,0.3874) & (0.2944,0.3549) & (0.4276,0.2230) \\ (0.2289,0.4938) & (0.3614,0.3921) & (0.3561,0.3035) & (0.3429,0.3524) & (0.3296,0.4210) \\ (0.3569,0.4611) & (0.3500,0.4970) & (0.3714,0.4044) & (0.4045,0.3713) & (0.3085,0.4970) \\ (0.3465,0.4768) & (0.3879,0.3851) & (0.3690,0.4308) & (0.3730,0.4458) & (0.3330,0.5102) \\ (0.3819,0.3016) & (0.2728,0.5111) & (0.4910,0.3714) & (0.2728,0.6508) & (0.2728,0.3714) \\ (0.3095,0.6010) & (0.4333,0.4413) & (0.3095,0.2817) & (0.1857,0.6010) & (0.4333,0.2817) \\ (0.3304,0.4413) & (0.3304,0.6010) & (0.1982,0.6010) & (0.4626,0.2817) & (0.4626,0.4413) \\ (0.4428,0.5572) & (0.4644,0.5356) & (0.4428,0.5572) & (0.4320,0.5680) & (0.4536,0.5464) \\ (0.3304,0.4413) & (0.3304,0.6010) & (0.4626,0.2817) & (0.1982,0.6010) & (0.4626,0.4413) \\ (0.2182,0.5377) & (0.5092,0.1679) & (0.3637,0.5377) & (0.3637,0.3528) & (0.2182,0.7226) \end{bmatrix}. \tag{28}$$

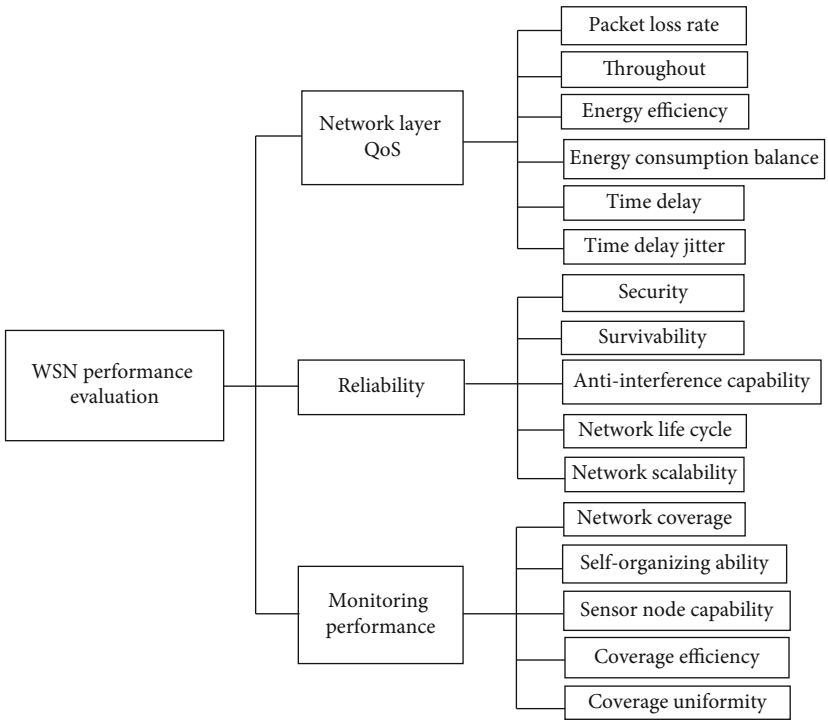

Figure 1: The preliminary evaluation indicator system.

Table 4: The decision table of the network layer QoS.

Expert serial number	Packet loss rate	Throughout	Energy efficiency	Energy consumption balance	Time delay	Time delay jitter	Network layer QoS
1	5	5	3	5	4	2	3
2	4	5	4	5	5	3	5
3	5	4	4	4	4	3	4
4	4	5	3	4	5	2	3
5	4	4	4	4	4	4	4
6	4	4	3	5	5	3	5
7	5	5	4	5	4	2	3
8	4	5	4	4	4	3	4
9	4	4	3	5	4	2	3
10	5	4	5	3	5	3	4

According to formulas (6) and (7), the intuitionistic fuzzy entropy weights of ten indicators are 0.0811, 0.0839, 0.0979, 0.0990, 0.0964, 0.0962, 0.1047, 0.1335, 0.1047, and 0.1025 in sequence. Suppose the weights of the subjective and objective weights are both 0.5, the combination weights of ten indicators are 0.0644, 0.0896, 0.0966, 0.0971, 0.0853, 0.1222, 0.1079, 0.1052, 0.1036, and 0.1282 in sequence. By using the aggregation operator, TOPSIS, VIKOR, GRA, and ER models, we get their evaluation results as shown in Table 7.

The results of these five single models are not consistent. In particular, the result of the VIKOR model is significantly different from those of the other four models, which may be caused by the fact that the VIKOR model considers individual regret factor at the same time. Kendall's coefficient of concordance equals 110, which is less than the critical value $s_{0.05}(5, 5) = 112.3$, so the five single evaluation models are not compatible. By removing a single model at a time, we get the statistical value of the remaining models as shown in Table 8.

Remove the VIKOR model, and Kendall's coefficient of concordance of the other four models equals 106, greater than the critical value $s_{0.05}(5, 4) = 88.4$, so the remaining four models are compatible. By applying the extremum transformation method, we convert the results of four single evaluation models into the range [0, 1]. By substituting the normalized values into the averaging, MSE-based weighted, and optimization combination models, we find that the optimal weights of four compatible models are all 0.25, indicating that the result of the optimization model is the same as that of the averaging model. Taking the averaging and MES-based

Table 5: The weights of indicators for WSN performance evaluation.

Primary indicator	Secondary indicator		
	Name	Implication	Composite weight
Network layer QoS (1/3)	Packet loss rate, C_1 (0.1429)	The number of packets lost during information transmission	0.0476
	Throughout, C_2 (0.2857)	Total data volume between gateway node and sensor nodes in the monitoring area	0.0952
	Energy efficiency, C_3 (0.2857)	The ratio of total energy consumption to throughput	0.0952
	Time delay, C_4 (0.2857)	Time difference between the first packet and the last packet to the gateway node	0.0952
Reliability (1/3)	Security, C_5(0.2222)	The ability of the network to guarantee the availability, confidentiality, authenticity, and integrity of the information	0.0741
	Survivability, C_6 (0.4444)	The ability of the network node to maintain its function under the condition of natural failure or intentional attack	0.1481
	Anti-interference capability, C_7(0.3333)	The ability of the network to resist the interference of adversary by electromagnetic energy and nonadversary	0.1111
Monitoring performance (1/3)	Network coverage, C_8 (0.2308)	Coverage of sensor nodes to the target monitoring area in WSN	0.0769
	Self-organizing ability, C_9(0.3077)	The ability of network nodes to determine their location and dynamically configure and manage themselves after deployment	0.1026
	Sensor node capability, C_{10}(0.4615)	The ability of sensor nodes to collect raw data, process local information, communicate wirelessly, route and forward, and work together with other nodes	0.1538

Note: the value in brackets is the weight of the indicator relative to the upper-level indicator.

Table 6: The original evaluation data.

Indicator	A_1	A_2	A_3	A_4	A_5
C_1	[0.2825,0.3030]	[0.1977,0.3134]	[0.2028,0.3320]	[0.1926,0.2996]	[0.1599,0.2063]
C_2	[1245,2016]	[1966,2421]	[1937,2774]	[1865,2579]	[1793,2306]
C_3	[0.42,0.51]	[0.45,0.52]	[0.38,0.49]	[0.36,0.45]	[0.45,0.59]
C_4	[0.0161,0.0197]	[0.0137,0.0176]	[0.0148,0.0185]	[0.0152,0.0183]	[0.0172,0.0205]
C_5	[high, highest]	[average, high]	Very high	Average	[average, very high]
C_6	Average	High	[average, very high]	[low, average]	[high, very high]
C_7	[average, high]	Average	[low, average]	[high, very high]	High
C_8	82%	86%	82%	80%	84%
C_9	[average, high]	Average	[high, very high]	[low, average]	High
C_{10}	[low, average]	[high, very high]	Average	[average, high]	Low

Table 7: The results of single evaluation models.

WSN	Aggregation operator		TOPSIS		VIKOR		GRA		ER	
	Comprehensive value	Rank	Proximity	Rank	Benefit ratio value	Rank	Relation degree	Rank	Belief degree	Rank
A_1	(0.3281,0.4954)	5	0.5026	5	0.8333	3	0.8979	5	(0.3214,0.5342)	5
A_2	(0.3805,0.4539)	3	0.5268	1	0.0000	1	0.9210	2	(0.3926,0.4745)	2
A_3	(0.3825,0.4162)	1	0.5253	2	0.3974	5	0.9228	3	(0.3785,0.4525)	1
A_4	(0.3425,0.4469)	4	0.5122	4	0.8687	2	0.9094	1	(0.3392,0.4998)	4
A_5	(0.3805,0.4312)	2	0.5138	3	0.4424	4	0.9100	4	(0.3758,0.4913)	3

Table 8: The statistical value of the remaining models by removing a single model.

The removed model	Kendall's coefficient of concordance
Aggregation operator	78
TOPSIS	58
VIKOR	106
GRA	74
ER	64

Table 9: The results of combination evaluation models.

WSN	Averaging	MSE-based	Drift		Cooperative game	
			Averaging	MSE-based	Averaging	MSE-based
A_1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A_2	0.8932	0.8955	0.9470	0.9474	0.9186	0.9198
A_3	0.9844	0.9842	0.9834	0.9832	0.9859	0.9858
A_4	0.4254	0.4245	0.4107	0.4108	0.4188	0.4186
A_5	0.6300	0.6280	0.5722	0.5710	0.6042	0.6024

weighted models as the objective model, we get the results of the drift and cooperative game models. The results of six combination evaluation models are summarized in Table 9.

The ranking results of six combination evaluation models are identical, i.e., $A_3 \succ A_2 \succ A_5 \succ A_4 \succ A_1 \succ$. The average correlation coefficient is 0.775, indicating that the results of the combination evaluation models have great consistency with the single evaluation models. It can be seen that the combination evaluation can make full use of the evaluation information, overcome the shortcomings, and retain the advantages of each method, so as to realize the consistent fusion of different single evaluation models. According to the above ranking results, company H can give priority to A_3 as the WSN partner.

6. Conclusions

In this research, considering that the purposes and requirements of different enterprises for WSN performance evaluation are not the same, we propose a method of indicator selection based on the rough set. By consulting experts with Likert's five-level scale and using the attribute reduction method of the rough set, we can obtain a relatively small-scale WSN performance evaluation indicator system that reflects the individual experience and judgment of experts. In addition, based on the decision tables, we also calculate the subjective weights of indicators by using the concept of dependence.

Considering the mixed multiattribute characteristics of the indicators, we first transform the precise real numbers, interval numbers, linguistic variables, TFNs, and TrFNs into the unified form of IFNs. Then, we calculate the objective weights of indicators on the basis of intuitionistic fuzzy entropy. By the linear combination of subjective and objective weights, we get the comprehensive weights.

Based on the research progress of intuitionistic fuzzy MADM methods, we put forward five single evaluation models for WSN performance, including aggregation operator, TOPSIS, VIKOR, GRA, and ER models. In order to make full use of their results, we propose the thought and framework of combination evaluation. First, we perform the Kendall compatibility test to get the compatible model set. Second, we apply the averaging, MSE-based weighted, optimization, drift, and cooperative game models to perform the combination evaluation. Third, we carry out the Spearman consistency test to get the best combination evaluation result.

The case study proves that the proposed indicator selection method and the evaluation models are feasible and efficient. In practice, decision-makers can apply the thought and method in this paper for performance evaluation or optimal selection of WSN.

Even though this study considers the mingle multiple attributes in the WSN performance evaluation process, there still exist other expression forms of evaluation indicators that should be taken into consideration. For instance, the values of indicators may contain the other forms, such as hesitant fuzzy number, Pythagorean fuzzy number, picture fuzzy number, and spherical fuzzy number simultaneously, so finding the way of unifying them into a consistent form with little information distortion is necessary for the future. The rough set method is used for subjective weight determination in this study. Actually, in addition to this method, there exist other methods suitable for subjective indicator weighting. For instance, the analytic network process (ANP) can take the correlations among indicators at the same level into consideration. Therefore, integrating the rough set method and other subjective weighting methods to improve indicator weighting may also be another future research direction.

Data Availability

The gathered data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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