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Research Article

Risk Priority Evaluation for Power Transformer Parts Based on Intuitionistic Fuzzy Preference Selection Index Method

Jiang Minglin [1] and Haiping Ren [2]

[1]School of Business, Minnan Normal University, Zhangzhou 363000, China
[2]Teaching Department of Basic Subjects, Jiangxi University of Science and Technology, Nanchang 330013, China

Correspondence should be addressed to Haiping Ren; chinarhp@163.com

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The risk assessment of power transformer equipment can not only improve the safety and management level of transformer operation, but also reduce the operation and maintenance costs of the equipment on the basis of ensuring the overall reliable operation of the power system. As a result, it can enhance the rewards of assets investment. The quantitative analysis of power equipment risk often contains qualitative indicators that are difficult to quantify. These indicators have the characteristics of fuzziness. In order to improve the accuracy and reliability of risk assessment results, this paper proposed a new risk evaluation method based on intuitionistic fuzzy set. Firstly, language variables are transformed into corresponding intuitionistic fuzzy numbers. Secondly, a novel entropy of intuitionistic fuzzy set is established. Thirdly, a weighting method for determining each expert's importance is proposed based on the new propose entropy. Furthermore, an extended preference selection index is put forward under intuitionistic fuzzy environment. Finally, an example of the risk assessment of power transformer components is discussed to illustrate the effectiveness of the new risk evaluation method.

1. Introduction

Power transformer, a key device in the power system, is also the core of power grid energy conversion and transmission. The failure of the power transformer will affect the operation of the entire power grid. If the failure of the power transformer causes power outage, it will affect the economic benefits of the relevant power consumption units, leading to great economic losses [1, 2]. Therefore, it is necessary to evaluate the risk of power transformer components, find out the cause of power transformer failure, improve the correct rate of power transformer risk identification, and reduce the failure rate of power transformer components [3].

At present, some research on fuzzy risk assessment of power transformer has been reported. Wang et al. [4] used fuzzy multi-criteria decision method to evaluate the risk of power transformer. Li et al. [5] evaluated the risks of power transformers by combining fuzzy analytic hierarchy process and artificial neural network. They put forward the maintenance strategy of power transformer. Muhammad Arshad et al. [6] have obtained positive results by using fuzzy logic diagnosis and data interpretation techniques to assess the risks of power transformers, as well as to evaluate the remaining service life of power transformers. Khlebtsov et al. [7] combined theory with practice and developed a software by using fuzzy reasoning algorithms. This software can detect the risk of power transformer failure in the early stage and reduce the risk of power transformer failure. Flores et al. [8] used fuzzy risk index for power transformer failures caused by external faults. The above literature evaluate the fault risk of the whole power transformer, whereas they are less related to the risk assessment of the subsystems of power transformer components. Power transformer is the key equipment in the power system, and is also the core of power grid energy conversion and transmission. The fault of power transformer will affect the operation of the whole power grid. Therefore, it is necessary to evaluate the risk of power transformer components, find out the causes of power transformer failure, improve the accuracy of power transformer risk identification, and reduce the failure rate of power transformer components. Murugan and Ramasamy [9] constructed a health index (HI) method for power transformer maintenance, which based on the number of failures of 343 power transformer components in the Tamil nadu power corporation of India over an 11-year period. This method can effectively maintain the power transformer components and reduce the operating cost. Venkataswamy et al. [10] used a frequency and time domain system identification method and evaluated the risk of power transformer windings. Zhang et al. [11] used entropy weight fuzzy calculation to quantify the risk level of transformer equipment. They can accurately calculate the risk value of each component of the transformer and pertinently put forward the transformer maintenance strategy.

As can be seen from above, different methods have been applied to evaluate the risks of power transformer. However, there are still some remaining problems such as single data type. Because of the complex application scenarios of power transformers, accurate statistics are not available in many places. It is necessary to evaluate the risk of power transformer by considering mixed multi-generic information [12]. Fuzzy sets and linguistic terms are suitable for modelling some quality and uncertainty information. Intuitionistic fuzzy (briefly, IF) set, first proposed by Atanassov [13] is an extension of fuzzy set. Because the IF set simultaneously considers the information of true membership and false membership, it has stronger expressive ability in dealing with uncertain information. Hence, it can more finely describe the fuzzy essence of the objective world. Therefore, IF set theory has attracted more and more attention. For example, Li et al. [14] first established the evaluation index system of COVID-19's control toughness. Then based on this system, they proposed a comprehensive evaluation model based on IF set and TOPSIS method. Most image segmentation algorithms based on IF c-means clustering have some shortcomings, such as low final clustering accuracy, poor detail retention, large time complexity and so on. Wang et al. [15] proposed an IF c-means clustering algorithm based on distribution information, which is suitable for infrared image segmentation of the power equipment. Huang et al. [16] proposed a new IF distance measurement theory and developed a VIKOR -based risk evaluation method (based on the concept of maximum proximity) to solve the risk of power transformer components. More theories and applications of IF sets have been reported in literature [17–20].

As a matter of fact, due to the lack of data or materials, experts are hard to give specific fuzzy index of the risk score of power equipment components. To improve the results, it is more suitable to use uncertain data such as interval number, IF number and language number to prove such fuzzy indicator information, since the data are more informative.

In order to improve the accuracy and reliability of risk assessment results, this paper uses language variables to describe expert ratings. By transforming the language variables into corresponding IF numbers, a new IF entropy is proposed. Based on preference selection index (briefly, PSI) method, firstly proposed by Maniya and Bhaat [21], a new risk assessment method of power transformer components is presented. The advantage of the new PSI-based evaluation method is that it does not need to compare the importance of each evaluation scheme relative to each index, but sorts the alternative evaluation schemes by calculating the value of comprehensive preference index based on the statistical perspective [22]. When there are contradictions or conflicts between the relative importance of indicators, PSI method is more effective than others.

2. Preliminary Knowledge

2.1. Risk Assessment Objects and Indicators of Power Transformer Equipment. The statistical data of faults and defects of power transformers (with power ≥110 kV) in recent ten years provided by Zhao et al. [12] are shown in Figure 1. The fault defects of power transformer are divided into seven subsystems (respectively represented by $A1$-$A7$) according to the parts: winding, iron core, bushing, body, non-electric quantity protection, tap changer and cooling system. On this basis, according to the risk of components, the priority of chemical evaluation should be based on the value.

In equipment defect&trouble shooting and risk control, it is obviously not objective to determine the risk of its components only by the probability of failure and defect occurrence. Referring to [4, 23], this paper selects three indicators: occurrence degree, severity and detectability to conduct comprehensive quantitative risk assessment of transformer components.

Occurrence degree represents the probability and frequency of a certain type of fault that may occur when the system completes the functional task. Severity comprehensively represents the damage degree of the fault to the transformer, the impact on the operation of the equipment, the caused economic losses and the incurred repair costs. Detectability refers to the technical level and difficulty required for faults to be detected in advance under the existing operation and maintenance strategy. In order to reflect the diversity of indicator-attribution value expression and to cover more valuable decision-making information, the risk evaluation indicators with the above different characteristics are proposed to be processed as follows: the occurrence degree of components is accurately quantified in combination with the statistical data in Figure 1. However, due to the statistical historical data information, the given value may also have errors. Therefore, we can use interval numbers to describe it. Severity, which includes economic loss and repair cost, can be regarded as a semi-quantitative index by using the linguistic variables to describe the risk degree. As a qualitative index, delectability refers to the opinions of on-site experts and should be characterized by uncertain language variables.

2.2. Intuitionistic Fuzzy Theory and a New Established Entropy. In the following discussion, some basic concepts and operational laws will be recalled.

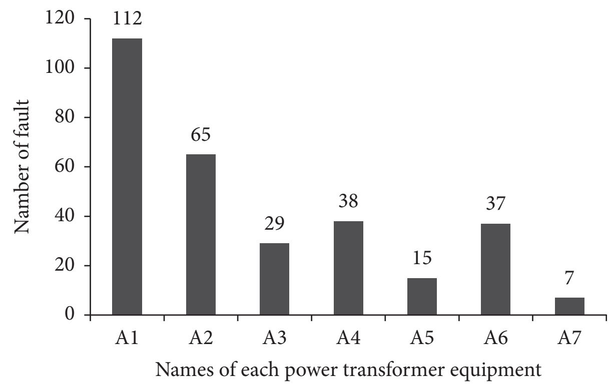

Figure 1: Fault numbers of power transformer equipment.

Definition 1 [see 13]. Let Ω be a given non-empty set. An IF set $\widetilde{P}$ is a set with the following form:

$$\widetilde{P} = \left\{ < \Delta_i, \mu_{\widetilde{P}}(\Delta_i), \gamma_{\widetilde{P}}(\Delta_i) > | \Delta_i \in \Omega \right\}, \quad (1)$$

where the mapping $\mu_{\widetilde{P}}\colon \Omega \longrightarrow [0,1]$ is named the membership degree function and $\gamma_{\widetilde{P}}\colon \Omega \longrightarrow [0,1]$ is named non-membership degree function. For all $\Delta_i \in \Omega$, it holds that $0 \leq [\mu_{\widetilde{P}}(\Delta_i) + \gamma_{\widetilde{P}}(\Delta_i)] \leq 1$. Furthermore, for an IF set $\widetilde{P}$, $\pi_{\widetilde{P}}(\Delta_i) = 1 - \mu_{\widetilde{P}}(\Delta_i) - \gamma_{\widetilde{P}}(\Delta_i)$ is named the hesitancy degree of Δ_i. We denote the set of all IF sets defined in Ω with the notation $IFSs(\Omega)$.

Remark 1. Xu and Chen [24] named $\widetilde{p}_i = < \Delta_i, \mu_{\widetilde{P}}(\Delta_i), \gamma_{\widetilde{P}}(\Delta_i) >$ as an IF number (IFN), and abbreviate it as $\widetilde{p}_i = \langle \mu_{\widetilde{p}_i}, \gamma_{\widetilde{p}_i} \rangle$, where $\mu_{\widetilde{p}_i} = \mu_{\widetilde{P}}(\Delta_i)$ and $\gamma_{\widetilde{p}_i} = \gamma_{\widetilde{P}}(\Delta_i)$ are the membership degree and non-membership degree of Δ_i belonging to $\widetilde{P}$, respectively. For an interval number $\widetilde{p}_i = [\mu_{\widetilde{p}_i}, 1 - \gamma_{\widetilde{p}_i}]$, it can be transformed in an IFN $\widetilde{p}_i = \langle \mu_{\widetilde{p}_i}, \gamma_{\widetilde{p}_i} \rangle$,

Definition 2 [see 13]. Let $\widetilde{P}$ and $\widetilde{Q}$ be two IF sets, $\widetilde{P} = \left\{ < \Delta_i, \mu_{\widetilde{P}}(\Delta_i), \gamma_{\widetilde{P}}(\Delta_i) > | \Delta_i \in \Omega \right\}$ and $\widetilde{Q} = \left\{ < \Delta_i, \mu_{\widetilde{Q}}(\Delta_i), \gamma_{\widetilde{Q}}(\Delta_i) > | \Delta_i \in \Omega \right\}$, then

(i) $\widetilde{P} \subseteq \widetilde{Q}$ if and only if $\mu_{\widetilde{P}}(\Delta_i) \leq \mu_{\widetilde{Q}}(\Delta_i)$ and $\gamma_{\widetilde{P}}(\Delta_i) \leq \gamma_{\widetilde{Q}}(\Delta_i)$ for all $\Delta_i \in \Omega$;

(ii) $\widetilde{P} = \widetilde{Q}$ if and only if $\widetilde{P} \subseteq \widetilde{Q}$ and $\widetilde{P} \supseteq \widetilde{Q}$;

(iii) The complementary set of $\widetilde{P}$ denoted by $\widetilde{P}^C$, where $\widetilde{P}^C = \left\{ < \Delta_i, \gamma_{\widetilde{P}}(\Delta_i), \mu_{\widetilde{P}}(\Delta_i) > | \Delta_i \in \Omega \right\}$,

(iv) $\widetilde{P} \prec \widetilde{Q}$ called $\widetilde{P}$ less fuzzy than $\widetilde{Q}$, i.e., for $\forall \Delta_i \in \Omega$,

① $\mu_{\widetilde{P}}(\Delta_i) \leq \mu_{\widetilde{Q}}(\Delta_i)$, $\gamma_{\widetilde{P}}(\Delta_i) \leq \gamma_{\widetilde{Q}}(\Delta_i)$, for $\mu_{\widetilde{Q}}(\Delta_i) \leq \gamma_{\widetilde{Q}}(\Delta_i)$,

② $\mu_{\widetilde{P}}(\Delta_i) \leq \mu_{\widetilde{Q}}(\Delta_i)$, $\gamma_{\widetilde{P}}(\Delta_i) \geq \gamma_{\widetilde{Q}}(\Delta_i)$, for $\mu_{\widetilde{Q}}(\Delta_i) \geq \gamma_{\widetilde{Q}}(\Delta_i)$.

Definition 3 [see 25]. Let E_n be a mapping, and E_n: $IFSs(\Omega) \longrightarrow [0,1]$, we call it an IF entropy of $\widetilde{P} = \left\{ < \Delta_i, \mu_{\widetilde{P}}(\Delta_i), \gamma_{\widetilde{P}}(\Delta_i) > | \Delta_i \in \Omega \right\}$, if it satisfies the following four conditions:

(C1) $E_n(\widetilde{P}) = 0$ if and only if $\widetilde{P}$ is a crisp set;

(C2) $E_n(\widetilde{P}) = 1$ if and only if $\mu_{\widetilde{P}}(\Delta_i) = \gamma_{\widetilde{P}}(\Delta_i)$, for $\forall \Delta_i \in \Omega$;

(C3) $E_n(\widetilde{P}) = E_n(\widetilde{P}^C)$,

(C4) If $\widetilde{P} \prec \widetilde{Q}$, then $E_n(\widetilde{P}) \leq E_n(\widetilde{Q})$.

Definition 4 [see 26]. Let $P_k = \langle \mu_k, \gamma_k \rangle \, (k = 1, 2, \cdots, L)$ be a collection of IFNs, and $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_L)^{\mathrm{T}}$ be the weight vector of $P_k \, (k = 1, 2, \cdots, L)$, where λ_k indicates the importance degree of P_k, satisfying $\lambda_k \geq 0 \, (k = 1, 2, \cdots, L)$ and $\sum_{k=1}^{L} \lambda_k = 1$, If

$$\psi_\lambda(P_1, P_2, \cdots, P_L) = \sum_{k=1}^{L} \lambda_k P_k = \langle 1 - \prod_{k=1}^{L} (1 - \mu_k)^{\lambda_k}, \prod_{k=1}^{L} \gamma_j^{\lambda_k} \rangle \quad (2)$$

then the function $\psi_\lambda(\cdot)$ is called the IF weighted aggregation operator.

In case other specified, in this paper $\widetilde{P} = \left\{ \langle \Delta_i, \mu_{\widetilde{P}}(\Delta_i), \gamma_{\widetilde{P}}(\Delta_i) \rangle | \Delta_i \in \Omega \right\}$ is assumed as an IF set with $\Omega = \{\Delta_1, \Delta_2, \cdots, \Delta_n\}$, To describe the fuzziness and uncertainty of IF set, some entropy measures of IF sets are put forward. Some entropy measures only consider the deviation between membership degree and non-membership degree, for example, Ye's IF entropy measure [27]:

$$E_n^Y(\widetilde{P}) = \frac{1}{n} \sum_{i=1}^{n} \left[\left(\sqrt{2} \cos \frac{\mu_{\widetilde{P}}(\Delta_i) - \gamma_{\widetilde{P}}(\Delta_i)}{4} \pi - 1 \right) \times \frac{1}{\sqrt{2} - 1} \right]. \quad (3)$$

Zeng and Li's IF entropy measure [28]:

$$E_n^Z(\widetilde{P}) = 1 - \frac{1}{n} \sum_{i=1}^{n} \left| \mu_{\widetilde{P}}(\Delta_i) - \gamma_{\widetilde{P}}(\Delta_i) \right|. \quad (4)$$

Zhang and Jiang's IF entropy measure [29]:

$$E_n^{ZJ}(\widetilde{P}) = -\frac{1}{n}\sum_{i=1}^{n}\left[\frac{\mu_A(\Delta_i)+1-\gamma_A(\Delta_i)}{2}\ln\left(\frac{\mu_A(\Delta_i)+1-\gamma_A(\Delta_i)}{2}\right)+\frac{\gamma_A(\Delta_i)+1-\mu_A(\Delta_i)}{2}\ln\left(\frac{\gamma_A(\Delta_i)+1-\mu_A(\Delta_i)}{2}\right)\right]. \quad (5)$$

Verma and Sharma's IF entropy measure [30]:

$$E_n^{VS}(\widetilde{P}) = \frac{1}{n(\sqrt{e}-1)}\sum_{i=1}^{n}\left[\left(\frac{\mu_A(\Delta_i)+1-\gamma_A(\Delta_i)}{2}e^{1-\frac{\mu_A(\Delta_i)+1-\gamma_A(\Delta_i)}{2}}+\frac{\gamma_A(\Delta_i)+1-\mu_A(\Delta_i)}{2}e^{1-\frac{\gamma_A(\Delta_i)+1-\mu_A(\Delta_i)}{2}}-1\right)\right]. \quad (6)$$

Because these entropy measures do not consider the influence of hesitation, there will be counter intuition in practical application. Some scholars have noticed this situation and considered the influence of hesitation in the construction of intuitionistic fuzziness, but there will still be special cases of counter intuition [31, 32].

In this paper, we will construct a new IF entropy measure with the following form:

$$E_n^{JY}(\widetilde{P}) = 1-\frac{1}{n}\sum_{i=1}^{n}\left[\left(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right)\times\left|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right|\right]. \quad (7)$$

Formula (7) can also be rewritten as follows:

$$E_n^{JY}(\widetilde{P}) = 1-\frac{1}{n}\sum_{i=1}^{n}\left[\left(1+\pi_{\widetilde{P}}(\Delta_i)\right)\times\left|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right|\right]. \quad (8)$$

The new established information measure $E_n^{JY}(\widetilde{P})$ not only considers the deviation $|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)|$, but also considers the hesitancy degree $\pi_{\widetilde{P}}(\Delta_i)$ of the IF set $\widetilde{P}$.

Theorem 1. *The information measure $E_n^{JY}(\widetilde{P})$ is an IF entropy.*

Proof. According to Definition 2, we know that if $E_n^{JY}(\widetilde{P})$ is an IF entropy, then it should satisfy the conditions ($C1$)-($C4$). Because, for all $a\geq 0, b\geq 0$, the inequality $a\times b \leq (a+b/2)^2$ is always true.

For $\forall\Delta_i\in\Omega$, let $a = 2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i) b = |\mu_{\widetilde{P}}(\Delta_i) -\gamma_{\widetilde{P}}(\Delta_i)|$, then

$$0\leq\left(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right)\times\left|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right|\leq 1. \quad (9)$$

In fact, it easily comes the conclusion:

$$0\leq\left(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right)\times\left|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right| \leq\begin{cases}\left(1-\gamma_{\widetilde{P}}(\Delta_i)\right)^2, \mu_{\widetilde{P}}(\Delta_i)\leq\gamma_{\widetilde{Q}}(\Delta_i),\\ \left(1-\mu_{\widetilde{Q}}(\Delta_i)\right)^2, \mu_{\widetilde{P}}(\Delta_i)\geq\gamma_{\widetilde{Q}}(\Delta_i).\end{cases} \quad (10)$$

Furthermore, $(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{Q}}(\Delta_i))\times|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{Q}}(\Delta_i)| = 1$, if and only if $\mu_{\widetilde{P}}(\Delta_i) = 1$ or $\gamma_{\widetilde{Q}}(\Delta_i) = 1$,

Then $0\leq E_n^{JY}(\widetilde{P})\leq 1$,

For the condition ($C1$),

$$E_n(\widetilde{P}) = 0$$
$$\Leftrightarrow\frac{1}{n}\sum_{i=1}^{n}\left[\left(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right)\times\left|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right|\right] = 1$$
$$\Leftrightarrow\left(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right)\times\left|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right| = 1, \forall\Delta_i\in\Omega. \quad (11)$$

The above formula is equivalent to

$$\mu_{\widetilde{P}}(\Delta_i) = 1, \gamma_{\widetilde{P}}(\Delta_i) = 0, \text{ or } \mu_{\widetilde{P}}(\Delta_i) = 0, \gamma_{\widetilde{P}}(\Delta_i) = 1. \quad (12)$$

That is, $\widetilde{P}$ is a crisp set.

For the condition ($C2$), (i) If $E_n(\widetilde{P}) = 1$, then

$$\frac{1}{n}\sum_{i=1}^{n}\left[\left(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right)\times\left|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right|\right] = 0. \quad (13)$$

This leads to the conclusion:

$$\left(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right)\times\left|\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i)\right| = 0, \forall\Delta_i\in\Omega. \quad (14)$$

Because $(2-\mu_{\widetilde{P}}(\Delta_i)-\gamma_{\widetilde{P}}(\Delta_i))\geq 1$, then the equation (14) is workable only if $\mu_{\widetilde{P}}(\Delta_i) = \gamma_{\widetilde{P}}(\Delta_i)$, for $\forall\Delta_i\in\Omega$;

Now, since $\mu_{\widetilde{P}}(\Delta_i) = \gamma_{\widetilde{P}}(\Delta_i)$, for $\forall\Delta_i\in\Omega$, it is obvious that $E_n(\widetilde{P}) = 1$.

For the condition ($C3$), it is obvious that $E_n(\widetilde{P}) = E_n(\widetilde{P}^C)$.

For the condition ($C4$), let $f(x,y) = (2-x-y)\times|x-y|$, where $x,y\in[0,1]$.

If $x\leq y$, then

$$f(x,y) = (2-x-y)\times(y-x), \quad (15)$$

leading to the partial derivatives of $f(x,y)$,

$$\frac{\partial f(x,y)}{\partial x} = 2x-2\leq 0, \quad \frac{\partial f(x,y)}{\partial y} = 2-2y\geq 0. \quad (16)$$

When $x \le y$, the function $f(x, y)$ decreases with x and increases with y, thus when

$$\mu_{\widetilde{Q}}(\Delta_i) \le \gamma_{\widetilde{Q}}(\Delta_i)\mu_{\widetilde{P}}(\Delta_i) \le \mu_{\widetilde{Q}}(\Delta_i)\gamma_{\widetilde{P}}(\Delta_i) \ge \gamma_{\widetilde{Q}}(\Delta_i), \quad (17)$$

then

$$f\left(\mu_{\widetilde{P}}(\Delta_i), \gamma_{\widetilde{P}}(\Delta_i)\right) f\left(\mu_{\widetilde{Q}}(\Delta_i), \gamma_{\widetilde{Q}}(\Delta_i)\right). \quad (18)$$

As a result,

$$\left(2 - \mu_{\widetilde{P}}(\Delta_i) - \gamma_{\widetilde{P}}(\Delta_i)\right) \times \left|\mu_{\widetilde{P}}(\Delta_i) - \gamma_{\widetilde{P}}(\Delta_i)\right| \ge \left(2 - \mu_{\widetilde{Q}}(\Delta_i) - \gamma_{\widetilde{Q}}(\Delta_i)\right) \times \left|\mu_{\widetilde{Q}}(\Delta_i) - \gamma_{\widetilde{Q}}(\Delta_i)\right|, \forall \Delta_i \in \Omega. \quad (19)$$

that holds $E_n(\widetilde{P}) \le E_n(\widetilde{Q})$,

Similarly, it can be proved that when $x \ge y$, $\partial f(x, y)/\partial x \ge 0, \partial f(x, y)/\partial y \le 0$, $f(x, y)$ will increase with x and decrease with y. Hence, when $\mu_{\widetilde{Q}}(\Delta_i) \le \gamma_{\widetilde{Q}}(\Delta_i)$, $\mu_{\widetilde{P}}(\Delta_i) \ge \mu_{\widetilde{Q}}(\Delta_i)$, as well as $\gamma_{\widetilde{P}}(\Delta_i) \le \gamma_{\widetilde{Q}}(\Delta_i)$ are satisfied, then

$$f\left(\mu_{\widetilde{P}}(\Delta_i), \gamma_{\widetilde{P}}(\Delta_i)\right) \ge f\left(\mu_{\widetilde{Q}}(\Delta_i), \gamma_{\widetilde{Q}}(\Delta_i)\right). \quad (20)$$

Therefore,

$$\left(2 - \mu_{\widetilde{P}}(\Delta_i) - \gamma_{\widetilde{P}}(\Delta_i)\right) \times \left|\mu_{\widetilde{P}}(\Delta_i) - \gamma_{\widetilde{P}}(\Delta_i)\right| \ge \left(2 - \mu_{\widetilde{Q}}(\Delta_i) - \gamma_{\widetilde{Q}}(\Delta_i)\right) \times \left|\mu_{\widetilde{Q}}(\Delta_i) - \gamma_{\widetilde{Q}}(\Delta_i)\right|, \forall \Delta_i \in \Omega, \quad (21)$$

which means $E_n(\widetilde{P}) \le E_n(\widetilde{Q})$ holds. □

Example 1. Let $\Omega = \{\Delta\}$ be a universal set with only one element, while $\widetilde{P} = \{\langle\Delta, 0.4, 0.5\rangle | \Delta \in \Omega\}$ and $\widetilde{Q} = \{\langle\Delta, 0.3, 0.4\rangle | \Delta \in \Omega\}$ are two IF sets. Then we can get

$$E_n^Y(\widetilde{P}) = E_n^Y(\widetilde{Q}) = 0.9895, E_n^Z(\widetilde{P}) = E_n^Z(\widetilde{Q}) = 0.9000,$$
$$E_n^{ZJ}(\widetilde{P}) = E_n^{ZJ}(\widetilde{Q}) = 0.9928, E_n^{VS}(\widetilde{P}) = E_n^{VS}(\widetilde{Q}) = 0.9905. \quad (22)$$

Obviously, $\widetilde{P}$ and $\widetilde{Q}$ have the same absolute value of deviation between membership and non-membership, but the hesitation degree is unequal. The hesitation degree of $\widetilde{P}$ is denoted by $\pi(\widetilde{P}) = 1 - 0.4 - 0.5 = 0.1$ and the hesitation degree of $\widetilde{Q}$ is $\pi(\widetilde{Q}) = 1 - 0.3 - 0.4 = 0.3$. Therefore, intuitively, the fuzziness of $\widetilde{P}$ is not equal to that of $\widetilde{Q}$. However, according to the entropy formulas (7)–(24), the entropy of $\widetilde{P}$ and $\widetilde{Q}$ are equal. Hence they are counter intuitive.

If we use the proposed entropy formula, we have

$$E_n^{JY}(\widetilde{P}) = 0.89, E_n^{JY}(\widetilde{Q}) = 0.87. \quad (23)$$

This overcomes the counter intuitive phenomena.

2.3. Intuitionistic Fuzzy Risk Assessment Model of Power Equipment Components. In the evaluation, decision-makers often uses simple and familiar language phrases (language variables) to make qualitative judgment on attributes. Because this evaluation method is more in line with the expression habits of decision-makers and can reflect the subjective will of decision-makers [33]. In order to facilitate decision-making, language variables are often quantified in decision-making process. In view of the superiority of IFNs in dealing with uncertain problems as well as the contained hesitation degree suitable for qualitative language information, many researchers convert language variables into corresponding IFNs [34]. The corresponding relationship of this transformation is given in Table 1.

IF entropy is defined in IF theory to reflect the fuzziness and uncertainty of sets. It depends on the overall reliability of the decision-makers. When there is information in the text, it depends on the overall reliability of the experts. When the degree of hesitation is more obvious, the experts are more familiar or have more information with the judged problem. As a result, the more confident and reliable the evaluation result is.

When each component to be evaluated forms a complete scheme set, let the overall IF entropy of expert k ($k = 1, 2, \ldots, L$) on the evaluation information of all attributes in the scheme set be [35]:

$$\lambda_k = \frac{1 - H_k}{L - \sum_{j=1}^{L} H_j}, k = 1, 2, \ldots, L, \quad (24)$$

where $H_k = 1/n \sum_{j=1}^{n} E_n^{JY}(\widetilde{p}_j^{(k)})$, $\widetilde{p}_j^{(k)}$ is the IF set composed of the evaluation value of each evaluation object given by the kth expert under j-th index, and $E_n^{JY}(\widetilde{p}^{(k)})$ is the proposed entropy defined in equation (7), which has the following mathematical formula:

$$E_n^{JY}\left(\widetilde{p}_{ij}^{(k)}\right) = 1 - \frac{1}{m} \sum_{i=1}^{m} \left(2 - \mu_{ij}^{(k)} - \gamma_{ij}^{(k)}\right) \times \left|\mu_{ij}^{(k)} - \gamma_{ij}^{(k)}\right|. \quad (25)$$

Now, we introduce the PSI method for risk assessment model of power equipment components under IF environment. First, find out all possible candidate evaluation objects and selection indices for the risk evaluation problem of power transformer equipment. Let $\Gamma = \{\Gamma_1, \Gamma_2, \cdots, \Gamma_m\}$ be a set of candidate evaluation objects, $\mathrm{I} = \{I_1, I_2, \cdots, I_n\}$ be a

Table 1: Corresponding table of language variable and IFN.

Language variable	Meaning of language variable	IFN
s_9	Extremely difficult/extremely serious	<0.95, 0.05>
s_8	Very difficult	<0.85, 0.10>
s_7	Difficult/serious	<0.75, 0.15>
s_6	Medium difficult/medium serious	<0.65, 0.25>
s_5	Medium	<0.50, 0.40>
s_4	Medium easy/medium trivial	<0.35, 0.55>
s_3	Easy/trivial	<0.25, 0.65>
s_2	Very easy/very trivial	<0.15, 0.80>
s_1	Extremely easy/extremely trivial	<0.05, 0.95>

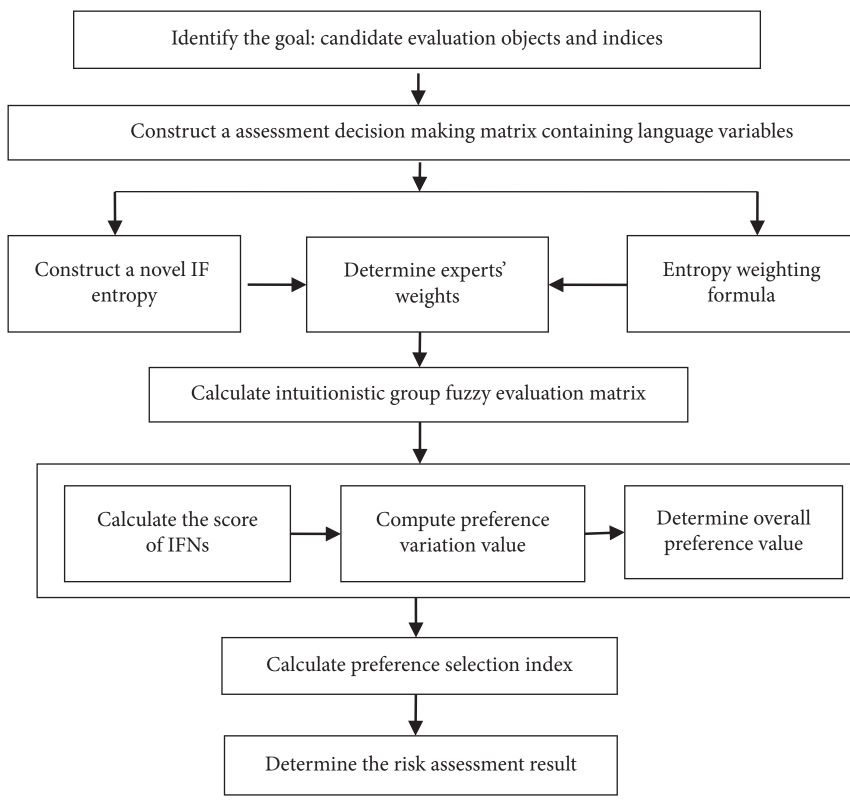

Figure 2: IF risk assessment model of power equipment components.

set of evaluation indices, where Γ_i is the i th object and o_j is the j th index. For kth expert ($k = 1,2, \ldots, L$), the evaluation values of alternative x_i ($i = 1, 2, \cdots, m$) on the attribute o_j ($j = 1, 2, \cdots, n$) is $\tilde{p}_{ij}^{(k)}$. Then the risk assessment problem can be modeled by the following evaluation matrixes:

$$\mathrm{P}^{(k)} = \left(\tilde{p}_{ij}^{(k)}\right)_{m\times n} = \begin{matrix} \\ \Gamma_1 \\ \Gamma_2 \\ \vdots \\ \Gamma_m \end{matrix} \begin{matrix} I_1 & I_2 & \cdots & I_n \\ \tilde{p}_{11}^{(k)} & \tilde{p}_{12}^{(k)} & \cdots & \tilde{p}_{1n}^{(k)} \\ \tilde{p}_{21}^{(k)} & \tilde{p}_{22}^{(k)} & \cdots & \tilde{p}_{2n}^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{p}_{m1}^{(k)} & \tilde{p}_{m2}^{(k)} & \cdots & \tilde{p}_{mn}^{(k)} \end{matrix}, k = 1, 2, \ldots, L. \tag{26}$$

and the detail calculation process is illustrated in Figure 2.

The detail calculation steps of the PSI Algorithm 1 can be described as follows.

Input: $\widetilde{p}_{ij}^{(k)}$: $k=1,2,\ldots,L$, $i=1,2,\cdots,m$ and $j=1,2,\cdots,n$.
Output: Preference selection index values Z_i, $i=1,2,\cdots,m$.
1: Transform the evaluation matrix $\mathrm{P}^{(k)}=(\widetilde{p}_{ij}^{(k)})_{m\times n}$ into IF evaluation matrix $\widetilde{R}^{(k)}=(\widetilde{r}_{ij}^{(k)})_{m\times n}$, where $\widetilde{r}_{ij}=\lambda_1\widetilde{r}_{ij}^{(1)}+\lambda_2\widetilde{r}_{ij}^{(2)}+\cdots+\lambda_L\widetilde{r}_{ij}^{(L)}$ according to equation (10).
2: Calculate the score matrix of $S=(S_{ij})_{m\times n}$, where $S_{ij}=\mu_{ij}-\gamma_{ij}$ is the score of $\widetilde{r}_{ij}=<\mu_{ij},\gamma_{ij}>$.
3: Compute preference variation value: $PV_j=\sum_{i=1}^{m}(S_{ij}-\overline{S}_j)^2$, where $\overline{S}_j=1/m\sum_{i=1}^{m}S_{ij}$.
4: Determine overall preference value: $\Psi_j=1-PV_j/n-\sum_{j=1}^{n}PV_j$, $j=1,2,\ldots,n$.
5: Calculate the PSI (Z_i) of i-th parts: $Z_i=\sum_{j=1}^{n}S_{ij}\times\Psi_j$, $i=1,2,\ldots,m$.

Algorithm 1: PSI algorithm for risk priority evaluation of power equipment components.

Table 2: The initial evaluation information of the risk of parts.

Parts	Probability of occurrence	Severity			Detectability		
		Expert 1	Expert 2	Expert 3	Expert 1	Expert 2	Expert 3
Winding ($A1$)	[0.35, 0.40]	s_9	s_8	s_8	s_5	s_6	s_6
Iron core ($A2$)	[0.20, 0.30]	s_9	s_9	s_8	s_7	s_6	s_5
Bushing ($A3$)	[0.05, 0.15]	s_7	s_7	s_6	s_5	s_3	s_4
Body ($A4$)	[0.10, 0.15]	s_7	s_6	s_7	s_3	s_3	s_5
Non electric protection ($A5$)	[0.01, 0.06]	s_5	s_6	s_5	s_6	s_5	s_7
Tap changer ($A6$)	[0.10, 0.15]	s_5	s_6	s_6	s_4	s_2	s_3
Cooling system ($A7$)	[0.01, 0.05]	s_3	s_2	s_3	s_2	s_4	s_4

Table 3: The intuitionistic fuzzy evaluation information provided by expert 1.

Parts	Probability of occurrence	Severity	Detectability
Winding	<0.35, 0.60>	<0.95, 0.05>	<0.50, 0.40>
Iron core	<0.20, 0.70>	<0.95, 0.05>	<0.75, 0.15>
Bushing	<0.05, 0.85>	<0.75, 0.15>	<0.50, 0.40>
Body	<0.10, 0.85>	<0.75, 0.15>	<0.25, 0.65>
Non electric protection	<0.01, 0.94>	<0.50, 0.40>	<0.65, 0.25>
Tap changer	<0.10, 0.85>	<0.50, 0.40>	<0.35, 0.55>
Cooling system	<0.01, 0.95>	<0.25, 0.65>	<0.15, 0.80>

Finally, we can evaluate the risk of all power equipment components according to the values of Z_i. Rank the power equipment component with highest risk situation if its PSI is the largest and the one is ranked last whose PSI is the smallest.

3. Numerical Example Analysis

Based on the historical statistical data of a region in recent years, the risk of a 220 kV power transformer component in the actual operation of the region is quantitatively analyzed by using the method in this paper. Firstly, three on-site experts are invited to give the fuzzy evaluation information of the severity and detectability of each independent component in combination with the operation of the transformer. At the same time, the occurrence index value is quantified in Figure 1, so as to obtain the initial evaluation decision information. See Table 2.

Step 1. By Remark 1 and Table 2, the IF evaluation matrixes can be provided in Tables 3–5:

Step 2. Calculate the weight of each expert, then

$$\lambda_1=0.3448,\lambda_2=0.3493,\lambda_3=0.3059. \tag{27}$$

Step 3. Gather the evaluation information of the experts shown in Tables 3–5, and get the IF evaluation matrix $\widetilde{R}=(\widetilde{r}_{ij})_{7\times 3}$ shown in Table 6.

Step 4. Calculate the score matrix of $S=(S_{ij})_{7\times 3}$:

$$S=\begin{pmatrix} -0.1250 & 0.4093 & 0.1551 \\ -0.2500 & 0.4341 & 0.2052 \\ -0.4000 & 0.2738 & -0.0733 \\ -0.3750 & 0.2698 & -0.1114 \\ -0.4650 & 0.1096 & 0.1952 \\ -0.3750 & 0.1551 & -0.2028 \\ -0.4700 & -0.2412 & -0.1694 \end{pmatrix}. \tag{28}$$

Table 4: The intuitionistic fuzzy evaluation information provided by expert 2.

Parts	Probability of occurrence	Severity	Detectability
Winding	<0.35, 0.60>	<0.85, 0.10>	<0.65, 0.25>
Iron core	<0.20, 0.70>	<0.95, 0.05>	<0.65, 0.25>
Bushing	<0.05, 0.85>	<0.75, 0.15>	<0.25, 0.65>
Body	<0.10, 0.85>	<0.65, 0.25>	<0.25, 0.65>
Non electric protection	<0.01, 0.94>	<0.65, 0.25>	<0.50, 0.40>
Tap changer	<0.10, 0.85>	<0.65, 0.25>	<0.15, 0.80>
Cooling system	<0.01, 0.95>	<0.15, 0.80>	<0.35, 0.55>

Table 5: The intuitionistic fuzzy evaluation information provided by expert 3.

Parts	Probability of occurrence	Severity	Detectability
Winding	<0.35, 0.60>	<0.85, 0.10>	<0.65, 0.25>
Iron core	<0.20, 0.70>	<0.85, 0.10>	<0.50, 0.40>
Bushing	<0.05, 0.85>	<0.65, 0.25>	<0.35, 0.55>
Body	<0.10, 0.85>	<0.75, 0.15>	<0.50, 0.40>
Non electric protection	<0.01, 0.94>	<0.50, 0.40>	<0.75, 0.15>
Tap changer	<0.10, 0.85>	<0.65, 0.25>	<0.25, 0.65>
Cooling system	<0.01, 0.95>	<0.25, 0.65>	<0.35, 0.55>

Table 6: The intuitionistic fuzzy evaluation information provided by expert 3.

Parts	Probability of occurrence	Severity	Detectability
Winding	<0.35, 0.60>	<0.8959, 0.0794 >	<0.6060, 0.2923>
Iron core	<0.20, 0.70>	<0.9293, 0.0622>	<0.6497, 0.2447>
Bushing	<0.05, 0.85>	<0.7220, 0.1763 >	<0.3735, 0.5247>
Body	<0.10, 0.85>	<0.7186, 0.1795>	<0.3402, 0.5576>
Non electric protection	<0.01, 0.94>	<0.5590, 0.3390>	<0.6432, 0.2510>
Tap changer	<0.10, 0.85>	<0.6060, 0.2923>	<0.2526, 0.6615>
Cooling system	<0.01, 0.95>	<0.2162, 0.6992>	<0.2894, 0.6229>

Table 7: The values of preference variation, overall preference variation and PSI.

Parts	Probability of occurrence	Severity	Detectability
Winding	<0.35, 0.60>	<0.85, 0.10, 0.05>	<0.65, 0.25, 0.10>
Iron core	<0.20, 0.70>	<0.85, 0.10, 0.05>	<0.50, 0.40, 0.10>
Bushing	<0.05, 0.85>	<0.65, 0.25, 0.10>	<0.35, 0.55, 0.10>
Body	<0.10, 0.85>	<0.75, 0.15, 0.10>	<0.50, 0.40, 0.10>
Non electric protection	<0.01, 0.94>	<0.50, 0.40, 0.10>	<0.75, 0.15, 0.10>
Tap changer	<0.10, 0.85>	<0.65, 0.25, 0.10>	<0.25, 0.65, 0.10>
Cooling system	<0.01, 0.95>	<0.25, 0.65, 0.10>	<0.35, 0.55, 0.10>

Step 5. Now, the results based on PSI method are obtained, and shown in Table 7.

Step 6. The vectors of preference variation value (PV_j) and the overall preference variation value (Ψ_j) are respectively obtained as:

$$PV_1 = 0.0920, PV_2 = 0.3138, PV_3 = 0.1919$$
$$\Psi_1 = 0.0908, \Psi_2 = 0.6862, \Psi_3 = 0.8081. \quad (29)$$

Step 7. The PSI (Z_i) are calculated as

$$Z_1 = 0.1218, Z_2 = 0.0985, Z_3 = -0.0976, Z_4 = -0.1022, Z_5 = -0.0788, Z_6 = -0.1656, Z_7 = -0.3035. \quad (30)$$

Then the risk priority of power transformer components is: Winding ($A1$) > Iron core ($A2$) > Non electric quantity protection ($A5$) > Bushing ($A3$) > Body ($A4$) > Tap changer ($A6$) > Cooling system ($A7$).

If we use VIKOR method proposed by Huang et al. [16], the result is: Winding ($A1$) > Iron core ($A2$) > Body ($A4$) > Bushing ($A3$) > Non electric quantity protection ($A5$) > Tap changer ($A6$) > Cooling system ($A7$). The results are almost consistent with the results of this paper. The advantage of this paper is that the PSI method itself does not need to determine the attribute weight.

4. Conclusions

Since the problems of quantitative and qualitative indicators in the risk assessment of power transformer components are difficult to be described by accurate numbers, this paper uses linguistic variables to describe expert scoring, and transforms linguistic variables into corresponding IF numbers. Furthermore, this paper proposes a new kind of IF entropy, develops an expert weight determination method based on entropy, and further proposes a risk assessment method of power transformer equipment based on PSI algorithm. Compared to the classical power equipment risk method, the method proposed in this paper can deal with the mixed multi-index evaluation problem where the index value is interval number, and language variable at the same time. This solves the problem that the index value is difficult to be accurately quantified. Hence, the evaluation model can cover more uncertain information, so as to effectively reduce the error caused by human subjectivity. At the same time, PSI method does not need to determine the weight of the evaluation index, and makes full use of the amount of information contained in the original data from the perspective of statistics, making the evaluation results more objective and reasonable. The example results preliminarily show the practicability and effectiveness of the method in this paper. The risk priority evaluation results can provide a basis for the power supply department to formulate and optimize the maintenance strategy. The method in this paper can also be used in many engineering problems, such as multi-attribute decision-making, material selection, partner selection and so on.

Data Availability

All data included in this study are included in this published article, and further details are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declared that they have no conflicts of interest to this work.

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