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Research Article

Research into Power Transformer Health Assessment Technology Based on Uncertainty of Information and Deep Architecture Design

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The uncertainty of the evaluation information is likely to affect the accuracy of the evaluation, when conducting a health evaluation of a power transformer. A multilevel health assessment method for power transformers is proposed in view of the three aspects of indicator criterion uncertainty, weight uncertainty, and fusion uncertainty. Firstly, indicator selection is conducted through the transformer guidelines and engineering experience to establish a multilevel model of transformers that can reflect the defect type and defect location. Then, a Gaussian cloud model is used to solve the uncertainty of the indicator criterion boundary. Based on association rules, AHP, and variable weights, the processed weights are calculated from the update module to obtain comprehensive weights, which overcomes the uncertainty of the weights. Improved DSmT theory is used for multiple evidence fusion to solve the high conflict and uncertainty problems in the fusion process. Finally, through actual case analysis, the defect type, defect location, and overall state of the transformer of the device are obtained. By comparing with many defect cases in a case-study library, the evaluation accuracy rate is found to reach 96.21%, which verifies the practicability and efficiency of the method.

1. Introduction

With the continuous development of China's electric power industry, the transformer remains an indispensable part of the transmission and distribution links therein. The stable and healthy operation of transformers is related to the reliability of power transmission, so the real-time health assessment of a transformer can ensure the safety and stability of power grid operation. There are many transformer components, and there are many indicators that can reflect the running state thereof. There is an inseparable relationship between each state indicator and between the indicators and the components. Therefore, the health assessment of the transformer should not only consider the reflection of the indicators on the operation of the transformer but also consider the correlation between the indicators [1]. The overall health assessment of a transformer entails uncertainty in the assessment process and conclusion, so it is necessary to research the uncertainty around transformer health from the perspectives of indicator criteria, weight setting, and information fusion.

In recent years, much research into the evaluation of transformer health conditions has been undertaken, among which the main idea is to determine transformer health conditions according to transformer monitoring data and running conditions [1–9]. The literature [1] proposes a state evaluation method using association rule analysis and variable weight coefficient and mines the deep relationship between single state quantity and comprehensive state quantity through copious field data. However, that work [1] is too absolute in terms of dividing the criterion boundary of the indicator and fails to consider the uncertainty of the boundary while neglects the multilevel structure of transformers and using a scoring method that is too simple. A previous study [3] proposes a defect diagnosis method of integrated set pair analysis and association rules and improves the weight setting and positive judgment rate based on association rules. However, the fuzzification function of the indicator is too rigid to conform to the actual function distribution and has the problem of no hierarchy. The state quantity fusion method also has certain defects. In reference [4], the fuzzy membership function is employed to describe the boundary uncertainty of the criterion, and the indicator is considered; however, the weight setting in [4] does not take actual failure cases into consideration. The DS evidence theory fusion used therein cannot solve the problem of high conflict existing in transformer state quantity data fusion. In view of the above analysis, the existing transformer state evaluation method still lacks a more practical and perfect system.

In view of the above problems, in the present research, a multilevel health assessment method is proposed for power transformers that account for information uncertainty. First, a deep architecture design of the equipment health assessment system was conducted, and a hierarchical assessment indicator system comprising an equipment layer, component layer, defect layer, and indicator layer was constructed. Then, based on the Gaussian cloud model, the degree of deterioration of the state indicators was evaluated, and the relative importance of the factors at each level is measured by combining the analytic hierarchy process, the association rule analysis method, and the deterioration variable weight method. Thereafter, improved DSmT theory is used to integrate the evaluated results from each level and reconcile any conflicts between the conclusions. Finally, the verification case study shows that the proposed method can be used to identify abnormalities in such equipment. This paper overcomes a previous problem whereby the evaluation obtained using the traditional method is insufficiently targeted. The new combination method of weights better reflected the true operating status of components and equipment. Based on the improved DSmT theory, this paper addresses the problem whereby traditional evidence theory cannot effectively integrate highly conflicting evidence.

2. Establishment of Assessment System and Process

2.1. Selection of State Indicators and Defect Types. The multisource heterogeneous indicator of a transformer includes real-time monitoring data, routine test data, infrared images, and other indices, which can reflect the operation of transformers from different perspectives and at different levels; therefore, it is the primary problem of the transformer state evaluation to select and process state quantity reasonably and accurately. At present, Guide for Condition Assessment of Oil-Immersed Power Transformers (Reactors) [10] and IEEE Guide for Assessment and Maintenance of Liquid-Immersed Power Transformers [11] are used as the benchmark for the construction of a state evaluation system, which covers the composition of state variables from different sources and forms of the transformer, taking into account the types of different indicators. Under the principle of guaranteeing the comprehensive acquisition of key parameters of transformers, 66 final transformer indicators are screened by association rules in this paper (Table 1). At the same time, the book information, defect information, historical defect, family defects, bad working conditions, operating environment, and other information about each transformer are also collected on site.

The deterioration of transformer health is usually accompanied by the occurrence of transformer defects. Therefore, the evaluation of transformer defect type can effectively help the operation and maintenance personnel discover problems with transformers. At the same time, solving transformer defects timeously and restoring transformers to a healthy condition can ensure the safe and stable operation of the power grid. Based on the distribution statistics of defect types of a large number of on-site defect cases and the experience of on-site personnel, we summarise 11 types of typical and frequent transformer defects (Table 2).

A transformer is a comprehensive and complex system, composed of multiple components. The evaluation results obtained by the simple fusion of all indices by the traditional method cannot reflect the multilevel differences in a transformer, and the evaluation accuracy is poor, so it is important to classify the evaluation levels according to the actual structure and mechanism of operation of the transformer under inspection [12]. From the perspective of components, the transformer can be divided into five parts: the body, bushing, on-load tap changer, cooler system, and nonelectric power protection device. Among them, the body and bushing are the main parts of transformer operation, and these two parts are subject to various stresses over a long time and are prone to failure, so the specific failure types of these two parts need to be considered; however, there is no clear defect classification for such a cooler system, on-load tap changer, and nonelectric power protection device in service, so the state can be directly reflected by other indicators.

2.2. Deep Architecture Design of the Transformer Evaluation System. Based on the above analysis, a multilevel comprehensive health assessment model of four layers, namely, the indicator layer, defect type layer, component layer, and equipment layer, is constructed, which represents the overall operating health condition of the transformer, operating conditions of transformer components, transformer defect type evaluation, and deterioration of multisource indicators of the transformer (Figure 1). The overall health condition of the transformer is the top layer, which is also the final evaluation result. The current operating health condition of the transformer can be judged by the evaluation result. Then, the whole system is divided into five parts: the body, the bushing, the on-load tap changer, the cooler system, and the nonelectric power protection device. The operating

Table 1: Distribution of transformer indicators.

Part	Single indicator	
Body	H_2 content	C_2H_2 content
	C_2H_4 content	C2H6 content
	CH_4 content	Total hydrocarbon content
	Absolute gas production rate of H_2	Absolute gas production rate of C_2H_2
	Absolute gas production rate of total hydrocarbon	Relative gas production rate of total hydrocarbon
	Absolute CO gas production rate	Absolute CO_2 gas production rate
	Initial difference of winding DC resistance	Imbalance rate of winding DC resistance
	Apparent discharge	Core grounding current
	Core insulation resistance	Polarization index
	Winding insulation resistance	Winding absorption ratio
	Initial difference of short-circuit impedance	Imbalance rate of short-circuit impedance
	Difference of winding voltage to initial value	Initial difference of winding capacitance
	Loss factor of oil medium	Furfural content
	Winding frequency response test	Insulation paper degree of polymerisation
	CO content	CO_2 content
	Water content in oil	Winding dielectric loss
Bushing	H_2 content	C_2H_2 content
	CH_4 content	Dielectric loss factor of bushing
	Initial difference of bushing capacitance	Insulation resistance of bushing end screen
	Insulation resistance of bushing	Infrared image analysis
	C_2H_4 content	Total hydrocarbon content
	Bushing leakage	Bushing oil level indicator
OLTC	Tap switch oil level indication	Oil filter for tap changer
	Tap changer respirator	Limit device of tap changer
	Tap position	Tap switch slide
	Tap leakage	Tap switch control loop
	Tap switch transmission mechanism	Action characteristics of tap changer
	Number of tap changers	Tap switch oil pressure
Cooler system	Oil flow relay state	Radiator working state
	Fan, oil pump, water pump state	Cooler system motor operation
	Cooler control system state	
Nonelectric protective device	Thermometer indication	Oil level indicator indication
	Gas relay malfunction	Pressure release valve malfunction
	Consistency from a distance	

Table 2: Distribution of defect types by component.

Part	Single defect	
Body	Winding interturn short circuit	Winding deformation
	Iron core multipoint grounding	Partial discharge
	Aging of oil paper insulation	Arc discharge
	Current circuit overheating	Wetted insulation
Bushing	Thermal performance of the bushing decreases	Insulation performance of the bushing decreases
	Mechanical performance of the bushing decreases	

condition of each part can be obtained through the evaluation. For the relatively important body and bushing, it is divided into defect type layer, including winding interturn short circuit, partial discharge, the thermal performance of the bushing decreases, and so on, and the distribution of grade membership degree of each defect type can be acquired by evaluation. The bottom layer contains many operating indicators pertinent to the transformer, corresponding to different defect types, respectively. The cooler system, on-load tap changer, and nonelectric power protection device directly correspond to the indicator layer.

3. The Uncertainty Information Processing Method

3.1. The Indicator Uncertainty Method Based on a Gauss Cloud Model. A transformer is a complex multilevel system, so the simple deterioration method based on warning value ignores the problem that the indicator criterion is too absolute and cannot truly reflect the uncertainty existing in the actual operation of a transformer. Therefore, Gaussian cloud processing is conducive to improving the accuracy of the evaluation [13].

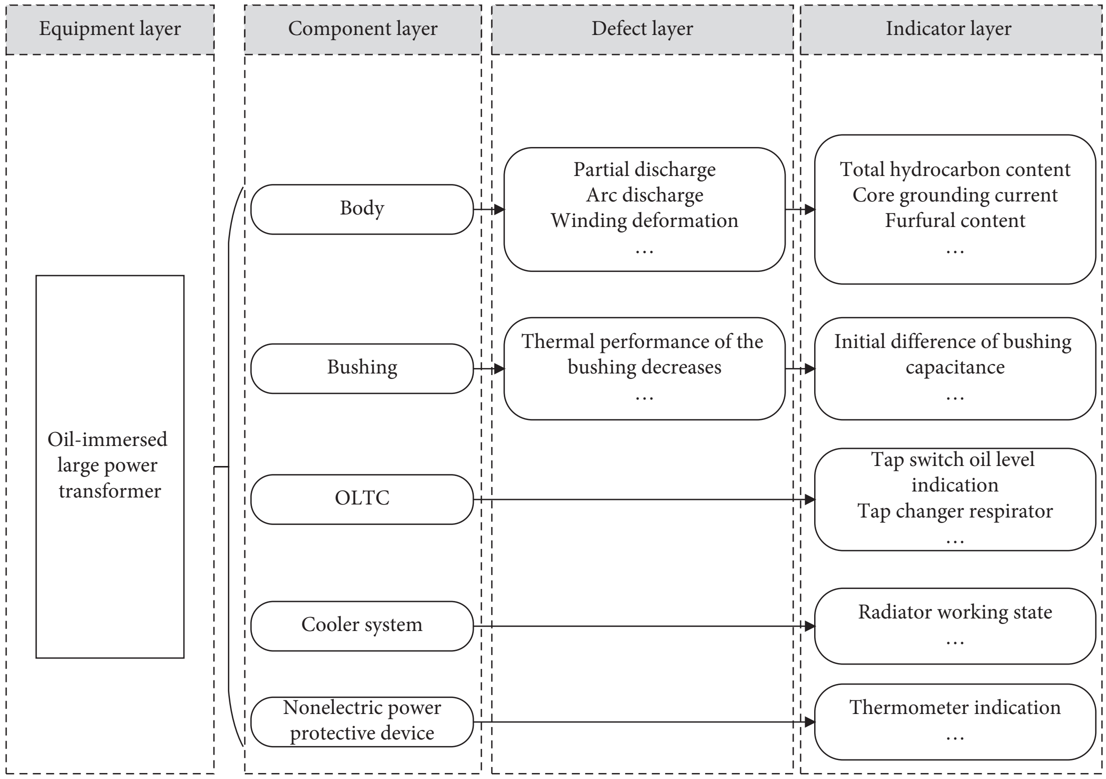

Figure 1: Transformer multilevel comprehensive architecture model.

3.1.1. Treatment of Deterioration of Indicators. There are many indicators of the transformer with different orders of magnitude, so here we use a relative degree of deterioration to normalise the indices. For structured data, it can be divided into a positive degradation indicator and negative degradation indicator according to whether it increases or decreases from normal to abnormal degradation. A positive deterioration indicator refers to the trend of increasing the value of a transformer indicator when it deteriorates, such as the grounding current of iron core and furfural content. A negative degradation indicator indicates that, when the indicator deteriorates, the value shows a decreasing trend, such as DC resistance.

A positive deterioration indicator is treated as in the followingequation:

$$x_{rt} = \begin{cases} \dfrac{X_{rt} - X_{rt0}}{X_{rta} - X_{rt0}}, & X_{rt0} \le X_{rt} \le X_{rta}, \\ 1, & X_{rt} \ge X_{rta}, \\ 0, & X_{rt} < X_{rt0}. \end{cases} \tag{1}$$

A negative deterioration indicator is treated as in the following equation:

$$x_{rt} = \begin{cases} \dfrac{X_{rt0} - X_{rt}}{X_{rt0} - X_{rta}}, & X_{rta} \le X_{rt} \le X_{rt0}, \\ 1, & X_{rt} < X_{rta}, \\ 0, & X_{rt} \ge X_{rt0}. \end{cases} \tag{2}$$

In (2), x_{rt} is the normalised degree of deterioration of the indicator, r is the number of defect types, t is the number of indices, X_{rt} is the measured value of the indicator, X_{rt0} is the initial value of the indicator, and X_{rta} is the warning value of the indicator. Its value refers to DL/T 596-1996 Preventive Test Rules for Electric Power Equipment, in which only the attention value is given in the regulation, and the warning value is converted by multiplying by 1.3 (positive deterioration indicator) or dividing by 1.3 (negative deterioration indicator). According to Guide for Condition Assessment of Oil-Immersed Power Transformers (Reactors) and the existing references, the health state of power transformers is generally divided into four grades, and the corresponding relationship with the deterioration degree of indicators is listed in Table 3.

Table 3: Classification of transformer state.

Level	Relative degree of degradation	Meaning
Normal	[0, 0.2]	Normal equipment: the transformer can run stably and healthily
Attention	(0.2, 0.4]	Suspicious equipment state: the transformer can continue to run under the premise of enhanced monitoring
Abnormal	(0.4, 0.7]	The equipment is in a poor condition or has minor defects
Serious	(0.7, 1]	Equipment has a serious failure and needs to arrange overhaul as soon as possible

3.1.2. Gaussian Cloud Model. In probabilistic terms, the Gaussian distribution is one of the most important and widely used probability distributions: the Gaussian membership function is the most commonly used membership function in fuzzy theory. The Gaussian cloud model uses the Gaussian distribution to realise the distribution of cloud titration values twice and uses the Gaussian membership function to realise random determination [14, 15].

Let U be a quantitative domain of precise numerical representation and $C(E_x\, E_n\, H_e)$ be a qualitative concept on U. If the quantitative value $x\in U$, and x is a random realisation of the qualitative concept C, x follows the Gaussian distribution with E_x as the expectation and E_{nn} as the variance, namely, x~N (E_x, E_{nn}). Among them, E_{nn} follows the Gaussian distribution with E_n as expectation and E_n as variance, i.e., E_{nn}~N (E_n, H_e), and the determinacy of quantitative value x to qualitative concept C is as follows:

$$y = \exp\left(-\frac{(x - E_x)^2}{2(E_{nn})^2}\right), \quad (3)$$

where x is the degree of deterioration of an evaluation indicator; E_x, E_n, and H_e are the mathematical characteristic values of a standard grade corresponding to the evaluation indicator; E_{nn} is a normal random number with expected value E_n and standard deviation H_e.

By constructing a forward cloud generator, a cloud drop sample diagram of $E_x = 1$, $E_n = 0.1$, and $H_e = 0.01$ is generated, in which the number of cloud drops is set to 500 (Figure 2). The envelopes of the cloud droplets represent the inner and outer correlation curves l_1 and l_2 of the Gaussian cloud, respectively, and the curve at the middle position is the expected curve l of the Gaussian cloud. The expressions of the three are as shown in equations (4) to (6):

$$l_1 = \exp\left(-\frac{(x - E_x)^2}{2(E_n - 3H_e)^2}\right), \quad (4)$$

$$l_2 = \exp\left(-\frac{(x - E_x)^2}{2(E_n + 3H_e)^2}\right), \quad (5)$$

$$l = \exp\left(-\frac{(x - E_x)^2}{2(E_n)^2}\right). \quad (6)$$

For a fixed cloud drop x, the intersection of the three curves represents the minimum correlation $y_{\min}$, the maximum correlation $y_{\max}$, and the expected correlation degree $y_{\exp}$ calculated by the extension cloud model: the size of the superentropy H_e represents the degree of deviation of the cloud droplet distribution from the Gaussian distribution, that is, the range of fluctuation of the correlation k is determined.

Based thereon, building a standard grade cloud model is a key step in the process of assessing the deterioration of state indicators. The extension cloud theory regards the hierarchical boundary as a double-constrained space $[c_{\min}, c_{\max}]$. After considering the uncertainty of the boundary value of the constrained space, it is appropriately expanded into a Gaussian cloud. According to the definition of cloud expectation, the central value of the constraint interval can best represent the concept of rank, so the calculation of grade cloud expectation E_x is as given in (7). As a measure of state-level concept ambiguity, the value of the level cloud entropy E_n is the most critical, and its size reflects the range of values that the state-level concept can accept, which will affect the adjudged indicator degradation. The calculation process is as shown in equation (8). The superentropy H_e of the grade cloud generally takes a fixed constant value, and this can be optimised and adjusted according to prevailing circumstances.

$$E_x = \frac{c_{\min} + c_{\max}}{2}, \quad (7)$$

$$E_n = \frac{c_{\max} - c_{\min}}{6}. \quad (8)$$

In the section of "Treatment of deterioration of indicators," the membership functions of the four states corresponding to the related indices can be calculated by using the aforementioned Gaussian cloud correlation function formula.

3.2. Weight Uncertainty Based on Comprehensive Weight Assignment Method. In transformer state assessment, weight setting is extremely important. Considering the limitations of the subjective weighting method and the objective weighting method, a method of weight combination of state indicators based on AHP and association rule analysis is proposed, making the assessment results better aligned with actual requirements.

3.2.1. Association Rules. An association rule is used to reveal the correlation between different indicators of an event. Based on data mining, an association rule finds the subset of indicators or attributes frequently occurring upon the occurrence of the event and the correlation between them through statistical rules [16, 17].

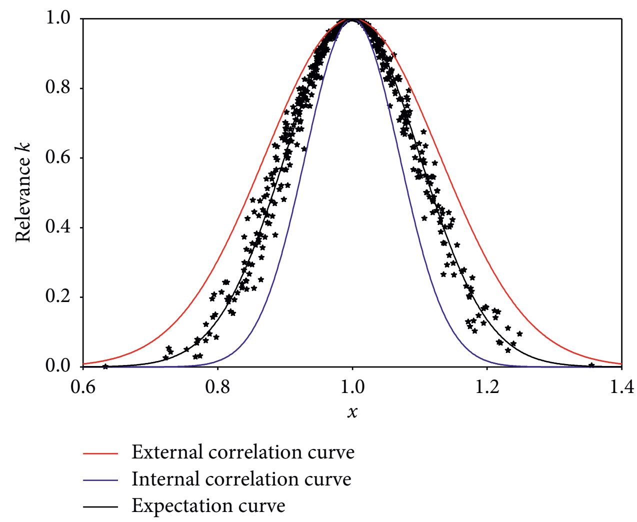

Figure 2: Gaussian cloud model.

In general, association rules between two events are calculated with support and confidence. Support is defined as hypothesis set $A \subset D, B \subset D$, and $A \cap B = \varnothing$. Support for association rule $A \cap B = \varnothing$ is the percentage of database D containing $A \bigcup B$, denoted as

$$\mathrm{Sup}\,(A \longrightarrow B) = P\left(A \bigcup B\right). \tag{9}$$

At this point, the closer the support is to 1, the stronger the relationship between occurrences A and B.

The confidence of association rule $A \longrightarrow B$ is the percentage of database D containing both A and B, that is, the conditional probability $P(B|A)$, denoted as

$$C\,(A \longrightarrow B) = P\,(B|A) = \frac{P\left(A \bigcup B\right)}{P\,(A)} \times 100\%. \tag{10}$$

Confidence represents the reliability of association rules, that is, the higher the confidence, the higher the reliability of A when B occurs; therefore, in transformer state assessment, if the severity of defects is described by the deterioration of indices, the objective weight of indices corresponding to each defect type should be judged by the degree of confidence. That is to say, the higher the confidence in a certain indicator is, the greater the influence of its deterioration on defects.

The confidence of each transformer indicator corresponding to the defect type can be calculated as follows:

(1) Transaction database $D=$ {any comprehensive overstandard state quantity}

(2) Event $A_{i,j}=$ {the j single state quantity in the i^{th} comprehensive state quantity exceeds the norm}

(3) Event $B_i=$ {type i defect occurrence}

In the system used here, when analysing a defect and its indicators, database D is item set B; therefore, according to (11), the degree of confidence of a defect association rule $A_{i,j} \longrightarrow B_i$ can be calculated as follows:

$$\begin{aligned} C\left(A_{i,j} \longrightarrow B_i\right) &= \frac{P\left(A_{i,j} \bigcup B_i\right)}{P\left(A_{i,j}\right)} = \frac{\sigma\left(A_{i,j} \bigcup B_i\right)/|D|}{\sigma\left(A_{i,j}\right)/|D|} \\ &= \frac{\sigma\left(A_{i,j} \bigcup B_i\right)}{\sigma\left(A_{i,j}\right)} \times 100\%. \end{aligned} \tag{11}$$

The degree of confidence of a single indicator in each defect type is calculated using equation (11), and then, the degree of confidence of each indicator in the same defect type is compared, and the constant weight coefficient of each indicator in this defect type is determined according to the degree of confidence of each indicator. The calculation is as follows:

$$w_{i,j} = \frac{C_{i,j}}{C_{i,1} + C_{i,2} + C_{i,j} + \cdots + C_{i,m_i}}, \tag{12}$$

where $w_{i,j}$ is the constant weight coefficient of the j^{th} single indicator in the i^{th} defect type and $C_{i,j}$ represents the confidence of the j^{th} single indicator in the i^{th} defect type. m_i is the number of single indicators contained in the i^{th} defect type.

3.2.2. Analytic Hierarchy Process. The analytic hierarchy process (AHP) is a multiobjective decision-making analysis method combining qualitative and quantitative components as formally proposed by Saaty in the mid-1970s. Its concept involves the combination of complex multiobjective decision-making techniques. The problem is hierarchical and standardised: the relevant factors are compared layer by layer, and the rationality of the comparison is tested layer by layer to provide credible analytical results. Therefore, in the present research, the analytic hierarchy process was used to determine the subjective constant weight of the state indicator, as follows:

Step 1. For an evaluation target involving n state indicators, industry experts construct judgment matrix A by comparing the importance of the state indicators according to the nine-level scale criterion, in equation (13), where a_{ij} is the relative importance score of state index i to state index j:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} = \left(a_{ij}\right)_{n\times n}. \tag{13}$$

Step 2. Calculation of the approximate weight ψ_i of each state index under the evaluation target. Commonly used calculation methods include the geometric average method and canonical column average method. The former is selected here, and the calculation process is as follows:

$$\psi_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{m=1}^{n} \sqrt[n]{\prod_{j=1}^{n} a_{mj}}}. \tag{14}$$

Step 3. To verify the rationality and validity of the weight distribution, a consistency test must be performed on the judgment matrix. The test is as given by equations (15) and (16). When CR < 0.1, the consistency test is successful; otherwise, the judgment matrix must be readjusted until it passes the consistency test:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \tag{15}$$

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1}. \tag{16}$$

In (16), $\lambda_{\max}$ represents the largest characteristic root of the judgment matrix; CI is the consistency index; RI is the average random consistency index, which is the sampling average of the consistency index, and its value can be found from standard tabulated values; CR represents the consistency ratio index.

Here, 428 sets of defect sample data of large power transformers rated at 66 kV and above are selected. The objective weight, subjective weight, and comprehensive weight of each indicator relative to each defect type are calculated by using association rules and AHP, as shown in the supplementary material (available here).

3.2.3. Variable Weight Coefficient. Variable weight theory is widely used and is an important modelling principle invoked in factor space theory. The following variable weight formula is introduced in the comprehensive health assessment of transformers:

$$w_i^v = \frac{\left(w_i/x_i\right)}{\sum_{p=1}^{n}\left(w_p/x_p\right)}, \tag{17}$$

where w_i^v is the variable weight coefficient of defect type i; x_i is the score of the defect type i; n is the number of defect types; w_i is the constant weight coefficient of defect type i.

Elsewhere [18], the equilibrium function is introduced into the form of the variable weight synthesis mode, and the variable weights are given by

$$w_i^v = \frac{w_i x_i^{1-\alpha}}{\sum_{p=1}^{n} w_p x_p^{1-\alpha}}. \tag{18}$$

In (18), α is an equilibrium function, $0 \le \alpha \le 1$, whose value depends on the relative importance of each defect type. When the degree of equilibrium of defect types is not high, take $\alpha > 0.5$; when serious defects of some comprehensive state variables are excluded, $\alpha < 0.5$; when $\alpha = 1$, the model degrades to the constant weight model. To maximize the influence of the deterioration of the evaluation factors on the overall evaluation of components and equipment, $\alpha = 0$ is used.

By introducing variable weight coefficients, the weight coefficient of state quantity can be automatically adjusted when severely degraded. This can better represent the state of deterioration of the transformer and meet engineering requirements at that time.

The comprehensive weight is calculated based on 428 defect cases, but it is difficult to maintain the accuracy of the evaluation for a long time based on the existing defect case database alone. Therefore, a self-updating module of weights is added to incorporate continuously new defect data into the database. This is then adjusted to achieve more accurate and comprehensive assessment results. When a new transformer defect occurs on site, the staff enter the defect-related data into the evaluation system. While assessing the transformer state, the database is also updated. The constant weights based on association rules will be recalculated and then changed. The updated comprehensive weights are processed and used as the basis for the next evaluation.

3.3. Transformer Uncertainty State Fusion Method Based on Improved DSmT. DSmT is a new fuzzy contradictory reasoning theory proposed by Dezert and Smarandache, which can be regarded as a natural extension of D-S evidence theory (Dempster–Shafer theory), but there are important differences between them. When the conflict between information sources is large, D-S theory often fails to merge or produces paradoxical results after fusion. DSmT can deal with the fusion of uncertain, highly conflicting, and inaccurate information sources that D-S cannot resolve [19, 20]. Considering that different states of the transformer have different weights, DSmT needs to be improved before being merged.

Considering that DSmT model constructed in this paper is constrained by completely exclusive conditions, it is necessary to be based on proportional conflict redistribution (PCR) rules. Distribute the conflict reliability generated in the fusion process to the synthetic reliability according to a certain ratio, so as to use the evidence more effectively. According to different allocation ratios, PCR rules are mainly divided into PCR1 to PCR6 rules, of which PCR6 is the most precise combination rule in mathematical logic [21].

The specific definition of PCR6 rules is as follows:

$$\begin{cases} \forall (A \neq \varnothing) \in D^{\Theta}, \\ m_{\cap}(A) = \sum_{\substack{X_1, X_2 \in D^{\Theta} \\ X_1 \cap X_2 = A}} m_1(X_1) m_2(X_2), \\ m_{PCR6}(A) = m_{\cap}(A)^2 + \sum_{i=1}^{M} m_i(A) \sum_{\substack{Y_{\sigma_i(k)} \cap A = \varnothing \\ \cap_{k=1}^{M-1} \left(Y_{\sigma_i(1)}, \ldots, Y_{\sigma_i(M-1)}\right) \in \left(D^{\Theta}\right)^{M-1}}} \left(\dfrac{\prod_{s=1}^{M-1} m_{\sigma_i(s)}\left(Y_{\sigma_i(s)}\right)}{m_i(A) + \sum_{s=1}^{M-1} m_{\sigma_i(j)}\left(Y_{\sigma_i(j)}\right)} \right). \end{cases} \tag{19}$$

In (19), M represents the number of evidence sources; $m_{\cap}(A)$ represents the combined reliability of the DSmT combination rule for A; $Y_s \in D^{\Theta}$ corresponds to the s^{th} evidence source; $m_s(Y_s)$ represents its corresponding reliability distribution function; σ_i represents that from 1 to M excludes i number, as shown in the following equation:

$$\begin{cases} \sigma_i(s) = s, & \text{if } s < i, \\ \sigma_i(s) = s + 1, & \text{if } s \geq i. \end{cases} \tag{20}$$

Considering that the above PCR6 combination rule is invoked to perform equal weight information fusion on multiple pieces of evidence and does not reflect the differences between different evidence sources, it can be considered that some priori information is ignored. In this case, direct fusion will lead to insufficient accuracy of evaluation; therefore, in the evaluation of the component layer and the equipment layer, the basic reliability distribution of each piece of evidence was adjusted by combining the weights of the evaluation factors reconciled by the variable weight coefficients. The specific process is as shown in (21); furthermore, by bringing the adjusted basic reliability distribution of each piece evidence into (19), the difference between sources of evidence is reflected in the fusion process, and the normalised synthetic reliability distribution is used as the final evaluated hierarchy.

$$m'(\cdot) = \omega_s m(\cdot). \tag{21}$$

In (21), ω_s represents the weight of the s^{th} evidence source after being adjusted by the variable weight coefficient.

Following the aforementioned process, the membership results of the main components and the transformer (as a whole) for each status level can be obtained. To avoid the problem of evaluation failure caused by the small difference between the grade membership values, reliability criteria are introduced to the final judgment of the overall health of components and equipment. It was assumed that the membership vector of the functional component or the entire device with respect to each state level is $h = [h_1, \ldots, h_4]$, where h_j represents the membership degree at the j^{th} state level. If it satisfies the condition given by equation (22), the health of the component or item of equipment is evaluated as being at the j^{th} state level and, among them, λ represents the confidence level. By referring to the common confidence level range [0.5, 0.7], λ is set to 0.55.

$$j = \min\left\{ j \mid \sum_{i=1}^{j} h_i \geq \lambda, \quad 1 \leq j \leq 4 \right\}. \tag{22}$$

4. Case Study of a Transformer Multilevel Health Model

Based on the above sections, a multilevel transformer health assessment model is established. The specific assessment of the model is as follows (Figure 3).

4.1. Case Study. Taking the 220 kV main transformer (SFPS9-150000/220) which has been in operation for 20 years in a certain substation as an example for verification, we collected basic account information, online monitoring indices, and experimental data pertaining to the evaluated transformer. Some of the state information collection in 2010 is summarised in Table 4.

Through analysis of the indicators that are found to have been degraded, the membership vector of each indicator corresponding to each level of the cloud model is calculated based on the Gaussian cloud model. Then, the objective weight of each indicator corresponding to each defect type is calculated based on association rules, and weight variation is performed. The first-level evaluation result is determined through weighted fusion, and the state of each defect type is obtained based on the reliability criterion. The grade membership degree of each defect type is listed in Table 5.

Based on the evaluation results of the first layer, it can be concluded that the iron core multipoint grounding defect of the body is in a serious state, which requires immediate

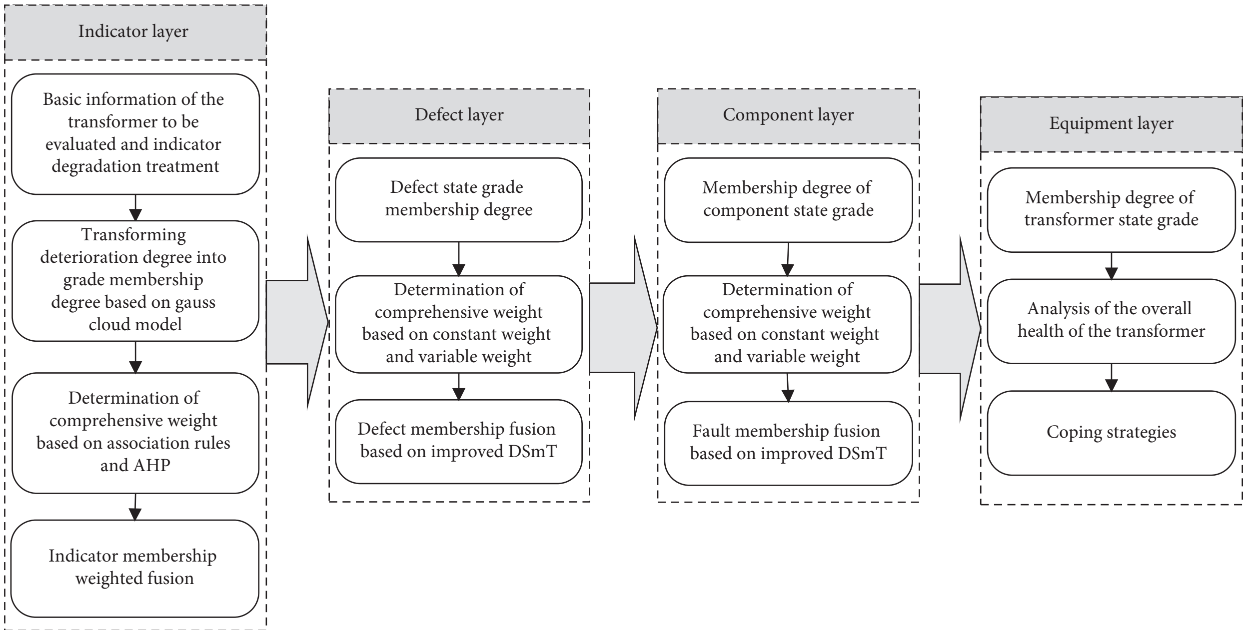

Figure 3: Multilevel health state evaluation model of a power transformer.

Table 4: Measured values of state indicators of transformer body.

State indicators	Measured value	Initial value
H_2 content	359	6.1
CH_4 content	18.5	8.7
C_2H_6 content	92	2.3
C_2H_4 content	52	4.8
C_2H_2 content	0	0
Total hydrocarbon content	162.5	15.8
Absolute CO gas production rate	12	0
Absolute CO_2 gas production rate	31	0
Core grounding current	3.8	0.01
Core insulation resistance	200	1 000
Winding absorption ratio	1.61	2
Polarization index	2.03	2.5
Imbalance rate of winding DC resistance	1.5	1
Initial difference of short-circuit impedance	1.2	1
Winding dielectric loss	0.36	0.17
Initial difference of winding capacitance	1.4	1
Apparent discharge	72	30
Water content in oil	12.1	3.5
Loss factor of oil medium	1.7	0.5
Furfural content	0.05	0
Insulation paper degree of polymerisation	900	1 000

power cutoff to repair related problems. At the same time, wetted insulation is in a state requiring attention which requires operation and maintenance personnel to strengthen the monitoring thereof.

Based on the degree of membership of each defect type and the indicator membership degree of the cooler system, OLTC, and nonelectric protective device, variable weight processing is conducted on the basis of an equal weight, and then improved DSmT fusion is used to obtain the degree of membership of each component grade, as listed in Table 6.

The grade membership of each transformer component is treated with variable weights. The membership vector of the overall condition of the transformer is derived by improved DSmT fusion, as shown in Table 7.

Based on the calculated results, the transformer body is in a serious state, and in terms of defect level, the evaluation of the iron core multipoint grounding corresponds to the "Severe" level, which differs from the evaluated status of other defect types. Therefore, the maintenance recommendation given is "need to arrange a power outage for overhaul as soon as possible". Operation and maintenance

Table 5: Grade membership of typical transformer defect.

Defect type	Normal	Attention	Abnormal	Serious	Condition
Interturn short circuit of winding	0.5590	0.0000	0.1487	0.2923	Normal
Iron core multipoint grounding	0.1196	0.0011	0.0002	0.8791	Serious
Arc discharge	0.6328	0.0002	0.0817	0.2853	Normal
Current circuit overheating	0.6702	0.0012	0.1207	0.2079	Normal
Winding deformation	0.6045	0.2112	0.0910	0.0933	Normal
Partial discharge	0.7497	0.0017	0.0001	0.2485	Normal
Aging of oil paper insulation	0.5925	0.1402	0.2673	0.0000	Normal
Wetted insulation	0.2699	0.5039	0.0297	0.1965	Attention

Table 6: Grade membership of transformer components in the example.

Part	Normal	Attention	Abnormal	Serious	Condition
Body	0.3516	0.0465	0.0170	0.5849	Serious

Table 7: The overall health of the transformer analysed.

Part	Normal	Attention	Abnormal	Serious	Condition
Equipment	0.3516	0.0465	0.0170	0.5849	Serious

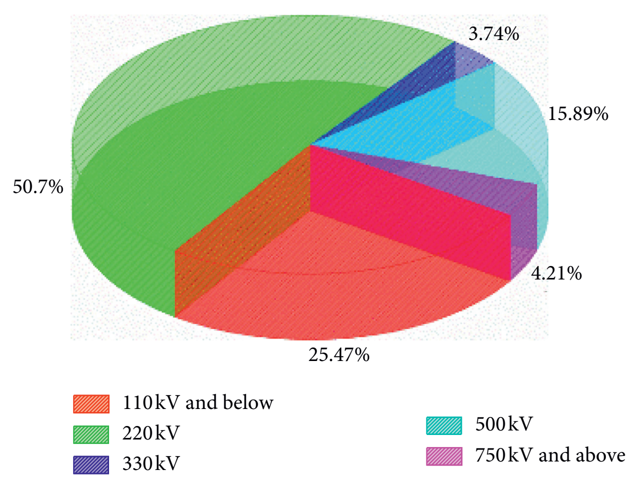

Figure 4: Statistical distribution of voltage levels.

personnel conducted a power outage inspection on the equipment and found metal powder at the bottom of the transformer oil tank. Under the action of electromagnetic attraction, a bridge was formed to connect the lower iron yoke to the feet or the bottom of the box, making the iron core unstable, and multipoint grounding then causes the iron core to overheat. The proposed method can be used to assess the health of power transformers and their functional components and provides detailed analytical results pertaining to the degradation of key components and possible defects.

4.2. Multiple Equipment Verification Analysis. In the "Case study" section, the usability and accuracy of the proposed method were verified based on a single device case. Here, 428 sets of measured data from multiple devices were used to conduct further group verification analysis. In the verification dataset, the voltage of the power transformer ranges from 66 kV to 1000 kV, and the specific statistical distribution thereof is shown in Figure 4; at the same time, the defects mainly appear on the body and bushing. The specific statistical distribution of these abnormalities is shown in Figure 5.

By using the proposed method to evaluate the aforementioned cases, the results of verification analysis on component defects are as listed in Table 8 and the results of verification analysis on the health status of components and equipment are given in Table 9. Accordingly, at the defect level, the overall accuracy of the proposed method as applied to component defect types reached 96.21%; at the component level, the accuracy of the resulting health status of the body, bushing, tap changer, and cooling system exceeds 90%; at the same time, at the equipment level, the accuracy of the overall health status of the transformer reaches 95.09%. However, at the defect level, the overall accuracy of the traditional deterministic method as applied to component defect types only reached 87.32%; at the component level,

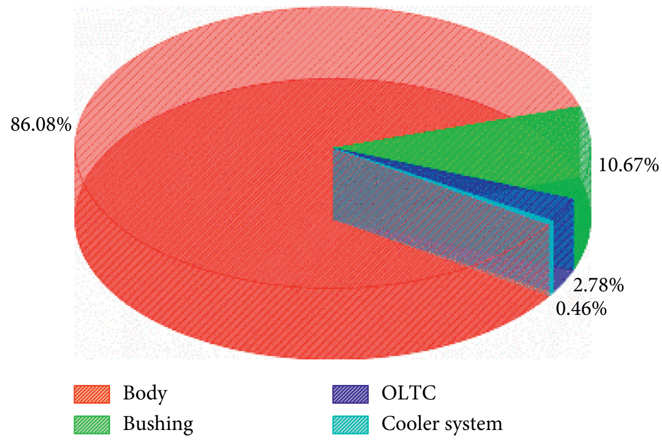

FIGURE 5: Statistical distribution of abnormal components.

TABLE 8: Verification of component defects.

Defect type	Evaluation accuracy
Interturn short circuit of winding	100
Iron core multipoint grounding	95.31
Arc discharge	97.87
Current circuit overheating	96.67
Winding deformation	98.48
Partial discharge	89.19
Aging of oil paper insulation	88.89
Wetted insulation	100
Thermal performance of the bushing decreases	92.31
Insulation performance of the bushing decreases	90.91
Overall	96.21

TABLE 9: Verification of the health condition of the transformer and its components.

Components	Evaluation accuracy (%)
Body	95.42
Bushing	91.30
OLTC	100
Cooler system failure	100
Overall	95.09

the accuracy of the resulting health status of the body, bushing, tap changer, and cooling system exceeds 75%; at the same time, at the equipment level, the accuracy of the overall health status of the transformer only reaches 85.87%. This shows that the multilevel health assessment method for power transformers based on the comprehensive treatment of information uncertainty can identify specific abnormal conditions more precisely as they occur in such equipment and provide targeted guidance for O&M personnel to formulate maintenance decisions.

5. Conclusion

A multilevel health assessment system consisting of an equipment layer, a component layer, a defect layer, and an indicator layer was established. By combining the various state indicators of the transformer from bottom to top, a step-by-step evaluation was undertaken to obtain a hierarchical evaluation, thus overcoming a previous problem whereby the evaluation obtained using the traditional method is insufficiently targeted.

A state indicator deterioration evaluation method based on the Gaussian cloud model was proposed, and the ambiguity measurement result pertaining to the degree of state indicator deterioration was obtained by applying flexible treatment to the grade criterion boundary.

Research into the combination of constant weights of state indicators based on AHP and association rules to avoid the limitations of subjective and objective weighting methods was undertaken; the introduction of variable weighting coefficients to reflect the influence of evaluation factor degradation on weight distribution was considered: this better reflected the true operating status of components and equipment.

Based on the improved DSmT theory, fusion analysis of relevant assessment factors was performed by redistributing the conflict information generated during the fusion process according to the PCR6 rules, so as to address the problem whereby traditional evidence theory cannot effectively integrate highly conflicting evidence. The final evaluation of comprehensive multisource information was thus obtained.

In summary, the proposed power transformer health assessment method can reveal the operating status of equipment from multiple perspectives and provide refined assessment conclusions, thereby helping O&M personnel make more targeted maintenance-related decisions.

Data Availability

The initial data of the dissertation mainly come from the project research. Some data have confidentiality agreements. Except for the data mentioned in the dissertation that can be disclosed, other data cannot be disclosed due to confidentiality issues.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

Supplementary Table: weight of each state indicators. (*Supplementary Materials*)

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