Research on Health Status Assessment of Distribution Transformers based on Information Fusion

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Abstract

A method for evaluating the health status of distribution transformers based on multi-information fusion is proposed. Combined with quantitative data, qualitative data and monitoring data, the constant weight of the indicators is calculated by the AHP method, and the degraded variable weight of the indicators is calculated by introducing the equilibrium function combined with the constant weight, so as to build a set pair analysis and improve the evidence theory of distribution transformer health Evaluate the model. The comprehensive connection degree of the set pair analysis and calculation index layer is used as an independent evidence body, and the evidence body is modified by improving the evidence theory and introducing the evidence deterioration factor and the timeliness factor. Then, the synthetic rules are used to integrate the information of quantitative indicators, qualitative indicators and monitoring indicators, and the comprehensive decision-making criteria are used to evaluate the health of distribution transformers. The feasibility of the health state assessment method proposed in this paper is verified through comparative analysis of examples.

Keywords

Distribution Transformer; Set Pair Analysis; D-S Evidence Theory; Health Status Assessment.

1. Introduction

As the end of the power network that supplies power to users, the distribution network directly faces the end users. The distribution transformer undertakes the tasks of transforming voltage, distributing and transmitting electric energy in the distribution network. In order to ensure the normal operation of distribution transformers, conduct in-depth researc h on key technologies that are conducive to the ability to prevent and respond to faults, such as health assessment of their operating status and operation and maintenance decisions, and provide advanced technical guarantees for the safe operation of distribution networks[1-3]. There are abundant research results on transformer state evaluation currently. For example, Du Jiang et al.[4] used association rules and gray cloud clustering to obtain the transformer fault layer state, and variable weight fusion was used to obtain the overall state of the transformer; Zhang Youpeng et al.[5] introduced expert evaluation. The results obtained by the AHP and AHP are subjective; Hao Sipeng et al.[6] obtained the comprehensive evaluation of the transformer based on the support vector machine and evidence theory by integrating the dynamic online monitoring and static preventive test data, but the abnormal monitoring data needs to be extracted. After establishing the indicator system of transformer insulation state, Liao Ruijin et al.[7] used the set-pair analysis theory and the method of connection degree to effectively deal with the uncertainty of transformer characteristic quantities, divided the system state, and obtained However, if the results of different feature quantities are directly weighted and fused, errors are prone to occur when the evaluation results of different feature quantities are quite different. There are also some literatures through artificial neural network[8], fuzzy comprehensive evaluation[9], gray target theory[10], cloud theory[11] and other methods to analyze the transformer state to achieve state evaluation.

Set pair analysis theory has the advantages of simple algorithm, intuitive evaluation and clear concept when dealing with uncertain systems, while D-S evidence theory is more flexible in the representation and measurement of information uncertainty. Therefore, this paper combines the abovementioned theories to establish hierarchical evaluation model for distribution transformers and adopts the method of set-pair analysis to determine the comprehensive connection degree of the first-level indicators, and takes it as the basic probability distribution of D-S evidence theory. Through D-S evidence theory fusion and revised evidence sources to obtain the evaluation results, so as to grasp the operation status of the transformer to ensure the safe and sTable operation of the distribution network.

2. Overall Architecture of Status Assessment

2.1. Establish an Evaluation Index System

Through the research on the formation mechanism of various faults of the transformer to accurately reflect the operating state of the distribution transformer, this paper refers to the State Grid Corporation's standards "Guidelines for Condition Maintenance of Distribution Network Equipment", "Guidelines for Condition Evaluation of Distribution Network Equipment" and existing research As a result, considering the operability of distribution transformer state assessment, a set of indicators including test information, operation information, inspection information, and online monitoring information is formed. The comprehensive state evaluation system of distribution transformer is shown in Fig. 1.

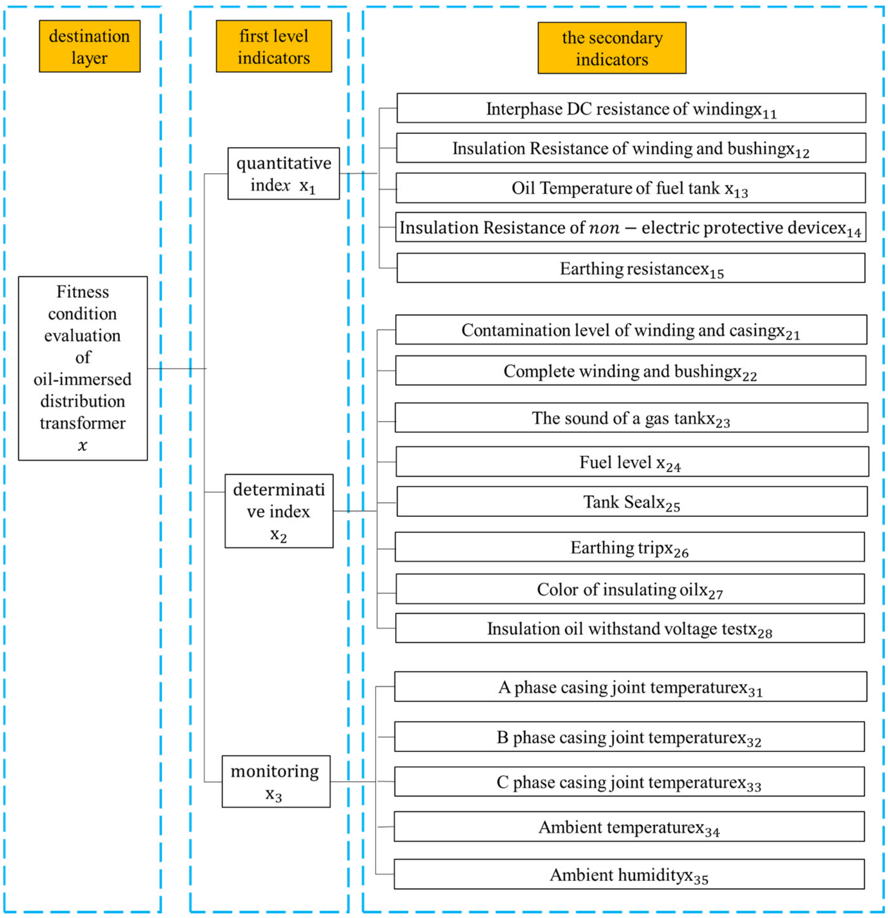

Fig 1. Comprehensive state evaluation system of distribution transformers

2.2. Indicator Normalization Processing

The order of magnitude and dimension of different indicators of distribution transformers are different. In order to eliminate the differences caused by different dimensions between the evaluation values of each indicator, and to make the evaluation values of all indicators comparable, they need to be normalized[12].

2.2.1. Quantitative Indicators

For the bigger is better indicator, the calculation formula is as follows:

$$x_{kl}=\begin{cases}\dfrac{X_{kl}-X_{attention}}{X_{good}-X_{attention}}, & X_{attention}<X_{kl}<X_{good}\\ 0, & X_{kl}\le X_{attention}\\ 1, & X_{kl}\ge X_{good}\end{cases} \tag{1}$$

For the smaller the better indicator, the calculation formula is as follows:

$$x_{kl}=\begin{cases}1-\dfrac{X_{kl}-X_{good}}{X_{good}-X_{attention}}, & X_{good}<X_{kl}<X_{attention}\\ 0, & X_{kl}\ge X_{attention}\\ 1, & X_{kl}\le X_{good}\end{cases} \tag{2}$$

Among them, x_{kl} is the normalized data of the index, X_{kl} is the measured value of the index, $X_{attention}$ is the attention value of the index, X_{good} is the good value of the index, and the good value and attention value of each index refer to DL/T 1753-2017 "Test Procedures for Condition Maintenance of Distribution Network Equipment".

2.2.2. Qualitative Indicators

Qualitative indicators are indicators that characterize a certain characteristic state of the transformer through state description, and specific data cannot be obtained. Before evaluation, the type needs to be quantified to adapt to the evaluation system. In order to avoid the subjective factor of scoring by technicians, refer to the "Guidelines for Status Evaluation of Distribution Transformers" for scoring. The scoring interval is $[0,1]$.

2.2.3. Monitoring Indicators

Online data has the characteristics of data flow, so the use of online data in state evaluation needs to consider the continuity of the data[13], this paper uses the sin function to process, the calculation method is as shown as below:

$$x_{kl}=\begin{cases}0.5-0.5\sin\dfrac{2\pi}{a}(X_{kl}-2a), & x<2a\\ 1, & x>2a\end{cases} \tag{3}$$

Among them, x_{kl} is the deterioration degree after the normalization of the index, X_{kl} is the value of the index at a certain time, a is the attention value of the index, and its value is set according to the warning of exceeding the limit value in the alarm information of the monitoring system. When the measured index value is closer to the attention value, it means that the state of the corresponding index is worse, and minor faults or faults are prone to occur. When the quantitative index value tends to be infinitely close to 2a, it means that the deviation of the index situation from the normal situation is extremely large. , it is necessary to carry out relevant field tests on the transformer immediately.

2.3. Classification of Evaluation Levels

There is no unified standard for the division of state evaluation levels of distribution transformers currently. In this paper, referring to the "Guidelines for State Evaluation of Distribution Network Equipment" and existing research results, the state levels of distribution transformers are divided into four levels, namely normal state, attention state, Abnormal state, critical state. Considering the needs of evaluation, the relative deterioration index is used to correspond to four state levels[6], and the threshold range is $[0,1]$, as shown in Table 1.

Table 1. Classification of Status Evaluation Levels

Status Level	Relative Degree of Deterioration	Performance Description
Normal z_1	(0.8, 1]	The overall operation is in good condition, the state quantity is sTable , and there is no need for maintenance soon
Attention z_2	(0.5, 0.8]	It can continue to run, the state quantity develops in the direction of the limit value, and the operation is usually monitored.
Abnormal z_3	(0.2, 0.5]	The performance is low, and the state quantity is close to or slightly exceeding the limit value. Arrange for maintenance, and power outage for maintenance if necessary.
Severe z_4	(0, 0.2]	The performance is very low, the state quantity seriously exceeds the limit value, and the power outage needs to be repaired as soon as possible.

2.4. Determination of Evaluation Weights

The AHP determines the constant weight, introduces an equilibrium function, and determines the variable weight of the index's deterioration[14]. The calculation formula is as follows:
The constant weight vector is

$$\omega_k^{(0)} = \left[\omega_{k1}^{(0)}, \omega_{k2}^{(0)}, \cdots, \omega_{kl}^{(0)}, \cdots, \omega_{kN_k}^{(0)}\right] \tag{4}$$

The variable weight of each parameter is

$$\omega_{kl} = \frac{\omega_{kl}^{(0)} x_{kl}^{\alpha-1}}{\sum_{l=1}^{N} \omega_{kl}^{(0)} x_{kl}^{\alpha-1}} \tag{5}$$

Among them, α is the variable weight coefficient, and α=0.2.
The variable weight vector is

$$\omega_k = \left[\omega_{k1}, \omega_{k2}, \cdots, \omega_{kl}, \cdots, \omega_{kN_k}\right] \tag{6}$$

3. Analysis and Identification of Monitoring Indicators

Traditional transformer condition assessment mostly uses static data. In recent years, with the improvement of performance requirements such as power supply reliability, online detection devices such as bushing temperature have been gradually applied to transformer condition monitoring, providing a dynamic data source for transformer condition monitoring. In response to these technological advancements, many studies have begun to explore how to more accurately use these data to assess the condition of transformers.

3.1. Judgment of Abnormal Data Set based on Sliding Window

This paper defines a sliding window with a time interval of w, and the data points in the sliding window are expressed as $h_w(x_t^{w}) = \{x_{t-w}, x_{t-w+1}, \ldots, x_t\}$, take the data points to be detected Q is x_t at time t. The specific abnormal data set establishment process is as follows:

(1) During the actual operation of the selected distribution transformer, the temperatures of the three-phase bushing joints of A, B, and C are a sequence of time. From the time starting point of the bushing joint temperature data, a fixed sliding window of length is added.

(2) Calculate the temperature adjacency difference in the adjacent time interval of the distribution transformer bushing joint temperature in the sliding window, as shown in formula (7).

$$\mathrm{lin}(x_t) = lin(x_{t-w}) - lin(x_{t-w+1}) \tag{7}$$

(3)Calculate the average distance from the center of the data point in the sliding window as shown in formula (8).

$$avg\left(x_t^{(w)}\right) = avg\left(d\left(x_{t-w}\right)\cdots, d\left(x_{t-2}\right), d\left(x_{t-1}\right)\right) \tag{8}$$

where $d\left(x_t\right)$ represents the distance from the data point x_t at time to the center of the data point.

(4) calculate $z_t = \left|d\left(x_t\right) - d\left(x_{t-1}\right)\right|$, As shown in formula (9).

$$avg\left(z_t^{(w)}\right) = avg\left(z_{t-w}, \cdots, \mathrm{z}_{t-1}, z_{t-1}\right) \tag{9}$$

Thus, the predicted value near the mean is calculated as

$$m_t^{(w)} = avg\left(x_t^{(w)}\right) + \frac{w}{2} avg\left(z_t^{(w)}\right) \tag{10}$$

(5) Set a specific threshold to τ ,if $\left|x_t - m_t^{(w)}\right| < \tau$,then the sliding window moves back one unit along the time series;if $\left|x_t - m_t^{(w)}\right| \geq \tau$, then the time point is marked as the data point at time, and the abnormal data set Q is added, and the distance of the data point at time $m_t^{(w)}$ is replaced by $d\left(x_t\right)$.

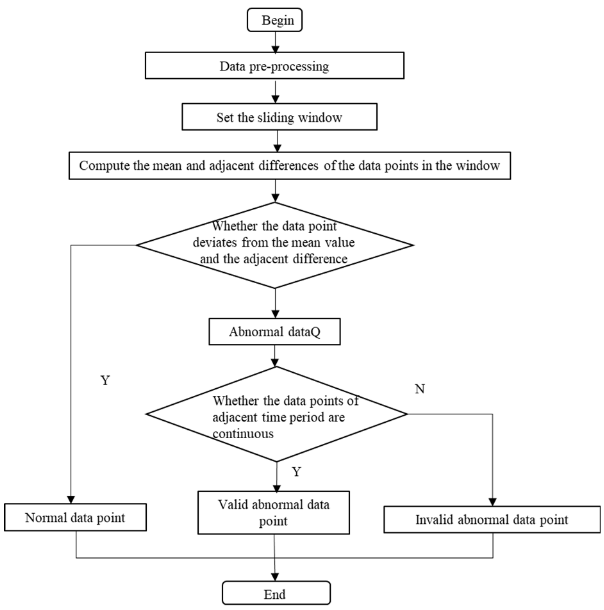

Fig 2. Flowchart of abnormal data identification

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(6) Repeat steps (2) to (5) ,until the screening of all time series data is over, and obtain a Q anomaly data set marked with time marks.

Abnormal data identification steps are shown in Fig 2.

4. Distribution Transformer Health Status Assessment Model

4.1. Evaluation Model of Transformer Index Layer based on Set Pair Analysis

Set pair analysis theory was proposed by Chinese scholar Zhao Keqin, which is suiTable for analyzing and dealing with uncertain systems. This method has the advantages of simple algorithm, intuitive evaluation, and clear concept. It has been used in high-speed railway catenary[17], wind speed prediction of wind farms[18], and wind turbine evaluation[19].

Set pair analysis is to study the connection between the two sets from three aspects: the same degree, the difference degree and the opposite degree between the two sets. Suppose two sets A_1 and A_2 are given, and$H=(A_1,A_2)$ is the set pair composed of them. In a specific context, the degree of connection is used to describe the set pair $H=(A_1,A_2)$, and their corresponding degree of connection is expressed as

$$\mu_H = a + bi + cj \tag{11}$$

Among them, i is the difference labeling coefficient, which takes a value in the interval $[-1,1]$, j is the opposite labeling coefficient, and the specified value is -1. a is the same degree, b is the difference degree, c is the opposite degree, the relationship between the three is a+b+c=1. a, c are relatively certain, b is relatively uncertain, and can be extended from ternary to $multi - K - ary\ connection\ degree$:

$$\mu_H = a + \sum_{t=1}^{K-2} b_t i_t + cj \tag{12}$$

In the formula, each parameter still satisfies the normalization condition, that is, $a + b_1 + b_2 + \cdots + b_{K-2} + c = 1$. b_t is the different grades of the difference degree, i_t is the labeling coefficient components with different degrees of difference.

Aiming at the evaluation index system of the health status of distribution transformers established in this chapter, a set pai $H(x_{kl}, z_t)$ between each evaluation index x_{kl} and the state level z_t is constructed, and each evaluation in the second-level index is constructed. The 4-element connection degree $\mu_{kl,1}$, $\mu_{kl,2}$, $\mu_{kl,3}$, $\mu_{kl,4}$ of the indicator and the state level of the distribution transformer can be calculated by the following formula and Fig 3 according to the fuzzy rule attribute Calculated.

$$\mu_{kl,1} = \begin{cases} 1, & x_{kl} \ge r_3 \\ \dfrac{2x_{kl} - r_3 - r_2}{r_3 - r_2}, & \dfrac{r_2 + r_3}{2} < x_{kl} < r_3 \\ 0, & x_{kl} \le \dfrac{r_2 + r_3}{2} \end{cases} \tag{13}$$

$$\mu_{kl,2}=\begin{cases}\frac{2x_{kl}-2r_3}{r_2-r_3}, & \frac{r_2+r_3}{2}<x_{kl}<r_3\\ \frac{2x_{kl}-r_1-r_2}{r_3-r_1}, & \frac{r_1+r_2}{2}<x_{kl}<\frac{r_2+r_3}{2}\\ 0, & x_{kl}\le\frac{r_1+r_2}{2}\text{或}x_{kl}\ge r_3\end{cases} \tag{14}$$

$$\mu_{kl,3}=\begin{cases}\frac{2x_{kl}-r_2-r_3}{r_1-r_3}, & \frac{r_1+r_2}{2}<x_{kl}<\frac{r_2+r_3}{2}\\ \frac{2x_{kl}-2r_1}{r_2-r_1}, & r_1<x_{kl}<\frac{r_1+r_2}{2}\\ 0, & x_{kl}\le r_1\text{或}x_{kl}\ge\frac{r_2+r_3}{2}\end{cases} \tag{15}$$

$$\mu_{kl,4}=\begin{cases}1, & x_{kl}\le r_1\\ \frac{r_1+r_2-2x_{kl}}{r_2-r_1}, & r_1<x_{kl}<\frac{r_1+r_2}{2}\\ 0, & x_{kl}\ge\frac{r_1+r_2}{2}\end{cases} \tag{16}$$

Among them, r_1, r_2, r_3 represent the threshold between each state level.

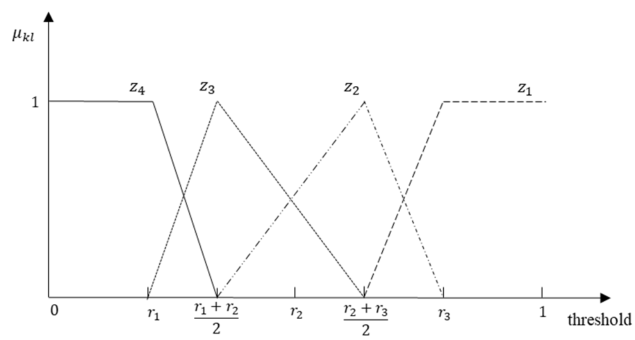

Fig 3. Schematic diagram of connection degree μ_{kl}

The set pair $H(x_k, z_t)$ between the k-th evaluation index x_k and the state level z_t in the secondary index of the distribution transformer health state evaluation index system, the corresponding connection degree is

$$\mu_{k,t}=\sum_{i=1}^{n}\omega_{kl}\mu_{kl,t} \tag{17}$$

4.2. Target-level Assessment based on D-S Evidence Theory

The information of different first-level evaluation indicators is fused through the D-S evidence theory to obtain the results of the health status evaluation of distribution transformers. The process is listed as below.

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4.2.1. Determining the Identification Framework

In the transformer evaluation system in this paper, the identification framework is $\Theta=\{z_1,z_2,z_3,z_4,\theta\}$, z_1,z_2,z_3,z_4 correspond to the four transformer state levels of normal, attention, abnormal and severe respectively, and θ is uncertain Spend.

4.2.2. Select Evidence and Determine the Basic Probability Distribution Function (BPA)

A sample space becomes a recognition frame Θ Θ, and 2^{Θ} is the set of all subsets of Θ , if the set function m: $2^{\Theta} \in [0,1]$, and the following conditions are satisfied:

$$\sum_{A\subseteq\theta} m(A) = A \tag{18}$$

$$0 \le m(A) \le 1, m(\varnothing) = 0 \tag{19}$$

In the formula, $m(A)$ is the basic probability distribution function of A, A is a subset of Θ, which becomes a focal element, and $\emptyset$ is an empty set.

In general, the function of the basic probability distribution function $m(A)$ is to map any subset A in the recognition frame Θ into a number $m(A)$ in the [0,1] interval.

4.2.3. Improvements to the Theory of Evidence

Considering from two aspects, the improvement of evidence theory is achieved by modifying the body of evidence.

1) The evaluation results did not show the deterioration phenomenon of a few indicators. Considering that a few indicators are at the abnormal level, and many indicators are at the normal level, the evaluation results of the normal level that are inconsistent with the actual operating state are obtained. theory to improve.

Use variable weights that can reflect the degree of deterioration of the indicators to modify the evidence body, so that the evidence body with serious deterioration occupies a larger proportion of the weight, so as to improve the evaluation results caused by serious conflicts between the evidence bodies.

The weighted sum of the variable weight of the secondary index and the degree of deterioration is recorded as the deterioration factor of the evidence body, and the formula is as follows [20]:

$$v_k = \sum_{l=1}^{L} \omega_{kl} x_{kl} \tag{20}$$

Among them, $v_k$is the deterioration factor of the th evidence body, ω_{kl} and $x_{kl}$are the variable weight and deterioration degree of the th index in the first-level index layer corresponding to the th evidence body, respectively.

The evidence body sensitivity factor is calculated by formula (21):

$$\rho_k = \omega_k^{(0)} v_k^{\alpha-1} / \sum_{k=1}^{K} \omega_k^{(0)} v_k^{\alpha-1} \tag{21}$$

Among them, ρ_k is the sensitivity factor of the k-th evidence body, $\omega_k^{(0)}$ is the constant weight of the first-level index layer, and the coefficient α=0.2.

When it is pointed out that the maximum value of the index weight is converted to 0.9, the priority reliability coefficient a of 0.9 will obtain a reasonable uncertainty reliability. Then there are:

$$\begin{cases} \varphi_k = \dfrac{\rho_k}{\max \rho_k} \\ \sigma_k = a\varphi_k \end{cases} \tag{22}$$

2) The sources of primary indicators are different. With the introduction of monitoring data, there are differences in timeliness between different indicators. Monitoring data is generally current data, quantitative data and qualitative data may be data from days or months ago.

The evidence validity factor γ_k of the test data is introduced, and the static indicators are processed dynamically by converting according to the detection time distance [6]. The formula is as follows:

$$\gamma_k = \frac{1}{1+t/T} \tag{23}$$

Wherein, t is the time (d) from the current moment, and the current moment is 0; T is the preventive test detection period; the monitoring indexγ_k value is 1.

This paper comprehensively considers the degree of evidence deterioration and timeliness factors, and defines a composite impact factor [21]:

$$\lambda_k = \sigma_k{}^{\beta} \gamma_k{}^{\varsigma} \tag{24}$$

Among them, β and ς are moderating factors, ς =0 when the time validity factor is not considered, and ς =1 when the evidence time validity factor needs to be considered. Likewise, β modulates the effect of deterioration factors on synthesis factors.

The corrected BPA is

$$\begin{cases} m_k(z) = \lambda_k \mu_{k,t} \\ m_k(\theta) = 1 - \sum_{t=1}^{4} m_k(z) \end{cases} \tag{25}$$

4.2.4. The Synthesis Rules of Evidence Theory

For a finite number of mass functions m_1, m_2,..., m_n, on $\forall A \subseteq \Theta$, Θ the Dempster synthesis rule is:

$$\left(m_1 \oplus m_2 \oplus \cdots \oplus m_n\right)\left(A\right) = \frac{1}{k} \sum_{A_1 \cap A_2 \cap \cdots \cap A_n = A} m_1(A_1) \cdot m_2(A_2) \cdots m_n(A_n)) \tag{26}$$

Among them,

$$\begin{aligned} K &= \sum_{A_1 \cap A_2 \cap \cdots \cap A_n \neq A} m_1(A_1) \cdot m_2(A_2) \cdots m_n(A_n) \\ &= 1 - \sum_{A_1 \cap A_2 \cap \cdots \cap A_n = A} m_1(A_1) \cdot m_2(A_2) \cdots m_n(A_n) \end{aligned} \tag{27}$$

4.2.5. Evaluation Decision

1)Reliability Criterion:

$$m\left(\theta\right) < \varepsilon_1 \tag{28}$$

where ε_1 =0.15. If it is not satisfied, the transformer operating state cannot be indicated.

2) The principle of maximum membership:

$$m\left(z_i\right) - m\left(z_j\right) > \varepsilon_2 \tag{29}$$

Among them, is the maximum value of BPA of the evaluation level, and is the second largest value of the BPA of the evaluation level, which is taken as ε_2 =0.15 in this paper; when formula (29) is satisfied, the evaluation result is level[22].

3) Accuracy principle: The transformer operating state level is obtained, then:

$$m\left(z_i\right) > m\left(\theta\right) \tag{30}$$

5. Case Analysis

In order to verify the validity and reliability of the evaluation method proposed in this paper, a distribution transformer with the model SBH15-M-315/10 in the urban area of a county-level city power supply company is selected for example verification, and combined with its quantitative indicators, Qualitative indicators and online monitoring indicators to comprehensively evaluate the operation of the equipment.

When an abnormal value alarm occurs on an online monitoring indicator, the latest offline indicator information data shown in Table 2 is retrieved.

Table 2. Distribution transformer index information data

Index	Measured value of indicators
Winding phase-to-phase DC resistance x_{11}	3.034/3.035/3.014Ω
Winding and bushing insulation resistance x_{12}	1343MΩ
Fuel tank temperature x_{13}	80℃
Non-electrical protection device insulation resistance x_{14}	1.24MΩ
Ground resistance x_{15}	4.3Ω
Winding and bushing contamination level x_{21}	no filth
Winding and bushing complete x_{22}	No damage
Fuel tank sound x_{23}	nothing unusual
Fuel tank level x_{24}	Show less oil
Fuel tank seal x_{25}	slight oil leakage
Ground down lead x_{26}	Appearance is normal
Insulating oil color x_{27}	very dark color
Insulating oil withstand voltage test x_{28}	Withstand voltage test qualified

5.1. Identification of Abnormal Indicators

Extract the online monitoring data from 9:00 on July 31, 2021 to 9:00 on August 1, 2021 (240 data in total). The monitoring data is sampled at a time interval of 6 minutes, and the temperature of the ABC three-phase bushing is extracted. for abnormal identification.Fig 4 shows the temperature data of ABC three-phase bushings.

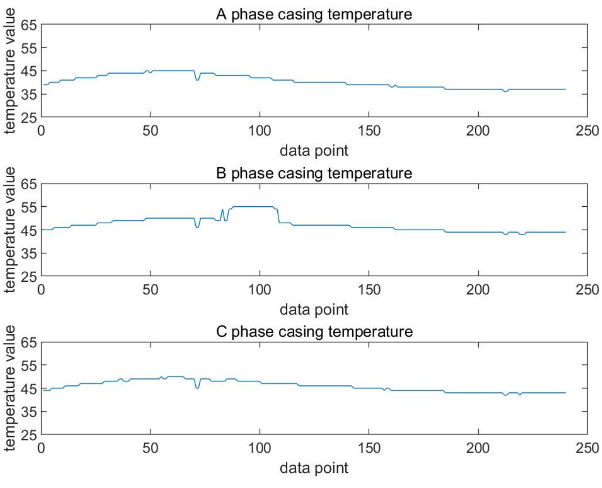

Fig 4. ABC three-phase bushing temperature data chart

By calculating the mean and adjacent difference of data points in each sliding window, if a point deviates from the average threshold, or there is a large difference between adjacent data, it indicates that the state of this data point is abnormal. Among them, 1 and 0 represent normal data points and abnormal data points, respectively.

In this paper, the abnormal identification of the ABC three-phase bushing temperature collected by the three sensors is carried out respectively. Fig. 5 to Fig. 7 show the identification diagrams of abnormal casing temperature data for Phase A, Phase B, and Phase C.

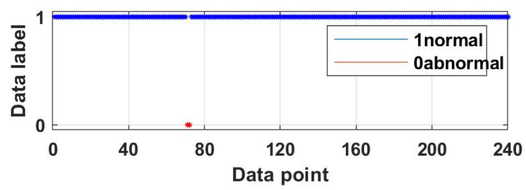

Fig 5. A-phase casing temperature abnormal data identification result

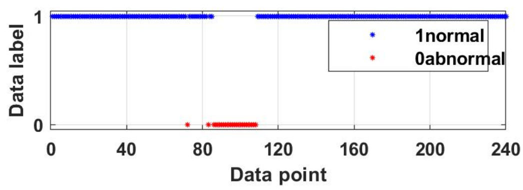

Fig 6. B-phase casing temperature abnormal data identification result

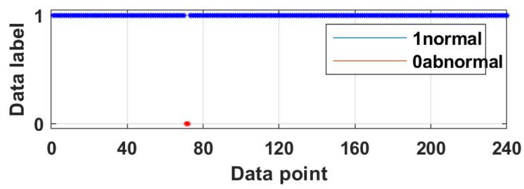

Fig 7. C-phase casing temperature abnormal data identification result

It can be seen from Fig. 5 and Fig. 7 that the temperature of the A-phase bushing and the C-phase bushing temperature of the distribution transformer are in normal state, and only a little abnormality occurs at T=72, which is judged as noise data. It is invalid abnormal data and can be ignored.

It can be seen from Fig. 6 that the temperature of the B-phase bushing of the distribution transformer has abrupt changes at T=72 and T=83, but the number of points is too small, and it is judged as noise data. There are multi-point continuous abnormal data near T=86, which belongs to the valid abnormal interval, indicating that the distribution transformer may be abnormal during this period, and its operation status should be evaluated as soon as possible. In practice, the intelligent diagnosis platform for the operation status of power distribution equipment developed by the research group shows that the temperature rise alarm of the B-phase bushing occurred in the equipment at 17:36 on July 31, 2021 (T=86). It has been verified that in actual operation, the positioning nut on the head of the B-phase bushing of the distribution transformer is loose, resulting in an increase in temperature. After the maintenance personnel locked the positioning nut, the temperature returned to normal.

5.2. Indicator Processing

According to the data in Table 2, the deterioration degree of qualitative and quantitative indicators can be obtained from equations (1) and (2), and the "Guidelines for Evaluation of Distribution Network Equipment"; according to the abnormal data identification results in Chapter 3, take T=86 -108 The monitoring data value in the continuous abnormal data interval is brought into formula (3) for calculation, and then the average value of the index quantity in this time period is taken for quantification processing; Variable weight, the results of index constant weight, variable weight and deterioration degree value are aggregated.

Table 3. Indicator weight Table

Index	$\omega_{kl}^{(0)}$	x_{kl}	ω_{kl}
x_{11}	0.3333	0.8792	0.3379
x_{12}	0.3333	0.9683	0.3128
x_{13}	0.1111	1.0000	0.1016
x_{14}	0.1111	0.8571	0.1150
x_{15}	0.1111	0.7167	0.1327
x_{21}	0.1992	0.9000	0.1982
x_{22}	0.3046	0.9000	0.3031
x_{23}	0.0646	0.9000	0.0643
x_{24}	0.0646	0.7000	0.0786
x_{25}	0.0646	0.9000	0.0643
x_{26}	0.0646	0.9000	0.0643
x_{27}	0.1188	0.6000	0.1635
x_{28}	0.1188	0.9000	0.1182
x_{31}	0.2157	0.9591	0.1279
x_{32}	0.4642	0.3327	0.6420
x_{33}	0.2157	0.7408	0.1572
x_{34}	0.0522	0.8558	0.0339

5.3. Calculation of Health Status Assessment of Distribution Transformers

5.3.1. Indicator Layer Evaluation based on Set Pair Analysis

Table 4. The calculated value of the relationship between the index quantity and the state level

First-Level Indicator	Second-Level Indicator	Degree of Connection			
		z_1	z_2	z_3	z_4
x_1	x_{11}	1.0000	0.0000	0.0000	0.0000
	x_{12}	1.0000	0.0000	0.0000	0.0000
	x_{13}	1.0000	0.0000	0.0000	0.0000
	x_{14}	1.0000	0.0000	0.0000	0.0000
x_2	x_{15}	0.4447	0.5553	0	0
	x_{21}	1.0000	0.0000	0.0000	0.0000
	x_{22}	1.0000	0.0000	0.0000	0.0000
	x_{23}	1.0000	0.0000	0.0000	0.0000
	x_{24}	0.3333	0.6667	0.0000	0.0000
	x_{25}	1.0000	0.0000	0.0000	0.0000
	x_{26}	1.0000	0.0000	0.0000	0.0000
	x_{27}	0.0000	0.8333	0.1667	0.0000
x_3	x_{28}	1.0000	0.0000	0.0000	0.0000
	x_{31}	1.0000	0.0000	0.0000	0.0000
	x_{32}	0.0000	0.0000	0.8847	0.1153
	x_{33}	0.6053	0.3947	0.0000	0.0000
	x_{34}	1.0000	0.0000	0.0000	0.0000

The set pair analysis method is used to calculate the degree of connection between each evaluation index and the health status level of the distribution transformer according to formulas (13)-(16). The calculation results are shown in Table 4.

According to formula (17), the comprehensive connection degree of quantitative index, qualitative index and monitoring index is calculated, and the calculation results are shown in Table 5.

Table 5. Calculation Results of Connection Degree

First-Level Indicator	Comprehensive Connection			
	z_1	z_2	z_3	z_4
x_1	0.9263	0.0737	0.0000	0.0000
x_2	0.8386	0.1887	0.0273	0.0000
x_3	0.2751	0.0829	0.5680	0.0740
weighted sum	0.5159	0.0928	0.3522	0.4550

It can be seen from Table 8 that the analysis and evaluation result of the weighted set is normal, and the abnormal phenomenon of the B-phase casing temperature in the monitoring index cannot be judged, and the accurate evaluation result cannot be obtained. Therefore, the following is an evaluation of distribution transformers through the improved evidence theory.

5.3.2. D-S Evidence Theory Evaluation based on Target Layer

The comprehensive connection degree obtained in the Table is used as the initial basic probability distribution function in the D-S evidence theory.

1) Correction of evidence deterioration degree

According to formula (20)-(22), the evidence body deterioration factor ν_k = {0.8952, 0.8843, 0.5097}, The evidence body sensitivity factor is ρ_k = {0.1987,0.0876,0.7137}, then σ_k ={0.2506,0.1105,0.9000}

2) Timeliness of evidence revision

Using formula (23) to correct the time validity of quantitative and qualitative indicators can improve the accuracy of evaluation. Considering that the quantitative indicators and qualitative indicators are the data obtained on July 6, 2021, T is 180 days, t is 117 days, and the substitution formula can be obtained $\gamma_1 = \gamma_2$ =0.6061.At this time, the adjustment factor ς takes 1. For the body of evidence k_3, ς is not necessary to consider the effect of evidence timeliness, so it takes 0.

3) Composite impact factor

According to formula (24), it can be known that λ_k ={0.1519,0.0670,0.9000}. According to formula (25), the basic probability distribution function after evidence correction is shown in Table 6.

Table 6. Basic probability distribution of modified sub-evidence bodies

Sub Body of Evidence	$m(\theta)$	BPA			
		z_1	z_2	z_3	z_4
x_1	0.8481	0.1407	0.0112	0.0000	0.0000
x_2	0.9293	0.0562	0.0127	0.0018	0.0000
x_3	0.1000	0.2476	0.0746	0.5112	0.0666

The sub-evidence bodies are fused according to formula (26)-(27), and the results are shown in Table 7 below.

Table 7. Revised sub-evidence body fusion results

Evidence	$m(\theta)$	BPA				Transformer Status
		z_1	z_2	z_3	z_4	
x_1&x_2&x_3	0.0922	0.3037	0.0708	0.4719	0.0613	z_3

It can be seen from Table 7 that it can be judged that the distribution transformer is in the z3-level state through the three decision-making criteria, that is, the abnormal state. Maintenance work should be arranged. After on-site verification, the actual situation of the transformer is that the temperature of the B-phase bushing abnormally rises at 17:36 on July 31, 2021, and the exceeding limit is 55 °C. At this time, the basic parameters of the transformer were analyzed, and it was found that the ambient temperature was 41 °C and the ambient humidity was 24. After verification, the positioning nut on the head of the B-phase bushing of the distribution transformer was loose, resulting in an increase in temperature. After the maintenance personnel locked the positioning nut, the temperature returned to normal.

6. Analysis of Evaluation Results

In order to verify the effectiveness of the method in this chapter, the evaluation results of the following cases are compared with the method in this chapter:

The health status assessment results of each method are shown in Table 8.

Table 8. Comparison of health status assessment results of various methods

Results	$m(\theta)$	$m(z_i)$				Transformer Status
		z_1	z_2	z_3	z_4	
Methods in this chapter	0.0922	0.3037	0.0708	0.4719	0.0613	z_3
traditional evidence theory	0.0000	0.9944	0.0056	0.0000	0.0000	z_1
untimed validity factor	0.0858	0.3456	0.0713	0.4402	0.0571	Uncertain

It can be seen from Table 8 that if $m(\theta)$ <0.1, the state of the transformer can be judged. The traditional evidence theory method cannot reflect the actual abnormal problems of distribution transformers. Although the method without considering the validity factor satisfies the reliability criterion, the difference of membership between normal state and abnormal state is less than the threshold that satisfies the principle of maximum membership, so the state of distribution transformer cannot be accurately judged. After adding the influence factor of timeliness, the real operating state of the distribution transformer can be accurately judged, and the dynamic processing of static test data and qualitative description is also realized.

Compared with these two cases, the method in this chapter can not only better deal with the situation that individual deterioration indicators are covered up by adding the influence factors of evidence deterioration degree and timeliness degree, but also realize the dynamic processing of static data to reduce the two categories. Therefore, the health status of distribution transformers can be accurately assessed, and the effectiveness of the method in this chapter is verified. At the same time, the method of integrating set pair analysis and evidence theory has the advantages of being simple and intuitive, the evaluation system is clear, and the state quantities are rich and varied, which provides a way of thinking for the health state evaluation of distribution transformers.

7. Conclusion

In the health status assessment of distribution transformers, set pair analysis is used to deal with the ambiguity of the index quantity. At the same time, the comprehensive connection degree constructed provides the basic probability distribution for the evidence theory, and the evidence deterioration degree factor is introduced to amplify the deterioration degree of individual indicators, so as to obtain a more Accurate evaluation results; introduce timeliness factor to dynamically process quantitative indicators and qualitative indicators, and integrate the corrected evidence body using synthesis rules to integrate evidence theory. The case analysis shows that the improved D-S evidence theory combined with the set pair analysis method makes the results obtained by the health status assessment more scientific and accurate, and also avoids the submersion of the deterioration degree of individual indicators, so that the results that are inconsistent with the actual situation can be obtained during the fusion.

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