Article citation info:
Shanyuan W, Donglin C, Zhonghong C, Menglong B, Hongyu O, Xiaoyang L, Weichao H, Changke C, Yangchen S. Research on transformer condition evaluation method based on association rule set pair analysis theory. Diagnostyka. 2023;24(4):2023410. https://doi.org/10.29354/diag/174869.

DIAGNOSTYKA, 2023, Vol. 24, No. 4

e-ISSN 2449-5220
DOI: 10.29354/diag/174869

RESEARCH ON TRANSFORMER CONDITION EVALUATION METHOD BASED ON ASSOCIATION RULE SET PAIR ANALYSIS THEORY

Wang Shanyuan [1,*], **Cai Donglin** [1], **Chen Zhonghong** [2], **Bai Menglong** [1], **Ouyang Hongyu** [1], **Lai Xiaoyang** [1], **Hu Weichao** [1], **Chen Changke** [1], **Shi Yangchen** [1]
1. State Grid Jinjiang Electric Power Supply Company, Jinjiang 362200, China
2. State Grid Dehua Electric Power Supply Company, Dehua 362500, China
[*]Corresponding author, e-mail: wsyneu@163. com

Abstract

Combining the advantages of set pair analysis and association rules, This paper proposes a transformer condition evaluation based on association rule with set pair analysis theory. In this paper, by analyzing the correlation between the various fault symptoms of transformer, a set of fault types is obtained. At the same time, this paper introduces variable weight formula based on the support degree and confidence degree of association rules, and finally the weight coefficients of fault types and fault symptoms are obtained. By comparing and calculating the support and confidence of association rules, while introducing variable weight formulas, the weight coefficients of fault types and fault symptoms are obtained. it effectively avoid the subjectivity of expert opinions or experiences. Based on the scalability of set pair analysis, a 5-element connection degree is adopted to improve the accuracy of handling uncertain factors in transformer fault diagnosis.

Keywords: transformer, set pair analysis, association rules, fault types, fault symptoms

1. INTRODUCTION

Combining the advantages of set pair analysis theory and the advantages of association rules for association evaluation. This paper focuses on 220kV transformer, a method of equipment condition evaluation based on set pair analysis theory of association rules is proposed on the basis of fully considering all relevant fault factors.

Power equipment data is the basis for evaluating equipment status [1]. This method mainly analyzes the correlation between transformer-fault symptoms, it normalizes the naming method about fault types according to the manifestation of fault symptoms, which calculate the confidence degree and support degree between fault symptoms in association rule theory. In the end, it introduces variable weight coefficient to obtain the similarity difference, so it inverse evaluation matrix of equipment status which fulled of related fault types and fault symptoms. Some chinese scholars provides a promising novel method for rapid on-site inspection of power equipment [2]. For the newly collected data, Shiqi Zhang proposed a method that the incremental learning of new fault modes is achieved by automatic feature extraction of the ResNet and the node expansion of the BLS.

The effectiveness of the proposed method is verified by data-driven from fault diagnosis [3].

Convolutional neural networks (CNNs) have promoted the development of diagnosis focus attention to insulation defect for gas-insulated switchgear (GIS) attribute to their excellent feature extraction and classification capabilities [4].

In terms of transformer status evaluation, known literature has formed a separate set of pairs for each test indicator which calculated by the connection, but it is not considered that the internal connections between various indicator quantities which determine the type of fault that occurred in the transformer. The Analytic Hierarchy Process (AHP) are used to construct a fuzzy judgment matrix which exist transformer set analysis, it cannot completely eliminate the subjectivity of expert systems [5].

In view of this, this article attempts to organically combine set pair analysis and association rules, and apply them to power transformer fault diagnosis. This method establishes a set of fault types by analyzing the correlation between various fault symptom parameters during transformer operation. By calculating the support and confidence of association rules, while introducing variable weight formulas, the weight coefficients of fault types and fault symptoms are obtained. It effectively avoid the subjectivity of expert opinions or experiences. Based

Received 2023-08-09; Accepted 2023-09-01; Available online 2023-11-03

on the scalability of set pair analysis, a 5-element connection degree is adopted to improve the accuracy of handling uncertain factors in transformer fault diagnosis.

The association rule method is essentially a method based on probability reasoning, which mainly describes the random uncertainty of the research object under certain conditions (such as infinite number of experiments). The evaluation of the operation status of power transformers is not only related to randomly uncertain factors, but also involve various factors such as fuzzy uncertainty caused by incomplete information. Set pair analysis (SPA) theory is a new mathematical theory for dealing with uncertainty. Its basic idea is to include certainty and uncertainty in the same system [6]. It study the certainty and uncertainty of objects from three aspects: identity, difference, opposite, in order to comprehensively depict the interrelationships, influences, and transformations between objects.

In view of this, this article attempts to organically combine set pair analysis and association rules, it aim to apply them to power transformer fault diagnosis [7]. The basic idea is to classify firstly and manage the typical state variables(fault types and symptoms) that can reflect the operating conditions of transformers in the big data pool for detection and monitoring.

Then, the association rule method is used to explore the correlation between fault types and fault symptoms, and its weight coefficient is determined to minimize the impact of subjective opinions of the expert system on the accuracy of the weight. Furthermore, the relative deterioration degree and membership degree in fuzzy theory are introduced to construct an evaluation matrix [8].

Based on set pair analysis theory, the multiple connection of each fault symptom with fault type are sequentially determined [9]. Next, the weight coefficients determined by association rules are combined to obtain the overall operating status of the transformer. Finally, transformer health status assessment and fault diagnosis are carried out [10].

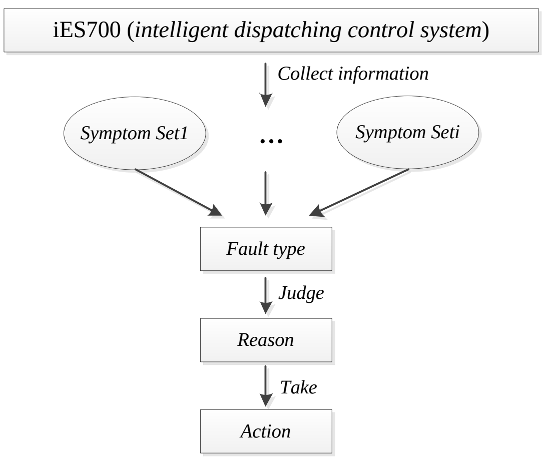

Fig. 1. Condition monitoring system of transformer

As shown in Figure 1, the intelligent dispatching control system collects the status information of the transformer, which obtains Fault type according to the alarm information of the equipment, and then we can find the reason according to the Fault type. Some machine design also studies this type of method [11].

Finally, the countermeasures are taken on this basis. Considering that the calculation of confidence is only associated with the data of the previous period, the calculation results can not be quickly reflected according to the real-time data, this chapter analyzed how to optimize the analysis model based on the association rule set. In some paper, ti also be called the impedance behavior [12].

The principle is to optimize the process performing secondary confidence based on the results of the calculation of constant weight. Its variable weight formula adjusts the coefficient according to the scoring results of each fault type, and the coefficient is adjusted in the range of [0, 1], When the coefficient is 0, the speed of changing weight is relatively gentle, and when the coefficient is 1, the speed of changing weight is relatively radical.

Variable weight involves historical data and real-time dynamic data, and its variable weight coefficient changes with the two types of data.

2. CONDITION EVALUATION SYSTEM OF TRANSFORMER

Combining the advantages in set pair analysis theory for uncertainty evaluation and the advantages in association rules for association evaluation, a method of equipment condition evaluation based on set pair analysis theory of association rules is proposed on the basis of fully considering all relevant fault factors. Due to the variety of equipment, the fault symptoms and types of each equipment are different, so this paper focuses on 220kV transformer, it could extend this method to the state assessment of other equipment.

This method mainly analyzes the correlation between transformer fault symptoms, which standardize the naming method of fault types according to the manifestation of fault symptoms. In the end, it could calculate the confidence degree and support degree of fault symptoms in association rule theory. It introduces variable weight coefficient to obtain the evaluation matrix of equipment status from fault types and fault symptoms, which avoid the subjectivity and fuzziness of experts in setting weights. In view of the accuracy of the evaluation formula, the multivariate relation degree theory of set pair analysis theory is introduced to improve the accuracy of uncertainty evaluation under equipment's condition above fault diagnosis.

Set pair analysis theory is an analysis method research based on system engineering and mathematical theory proposed by Zhao Keqin, a famous mathematician in China. Its method is characterized by clear logic, high calculation accuracy, and intuitive evaluation method. It is often used to deal with uncertainty problems caused by fuzzy objectives and incomplete information. Its theory has great advantages in more complex evaluation systems. Now, with the improvement of the set pair analysis theory itself, it is often used in the research of power equipment risk assessment, basin water resources assessment and other important scientific research fields.

Set pair analysis (SPA) theory is often used to deal with system engineering problems of uncertainty evaluation. Its main idea combined certainty evaluation and uncertainty evaluation in the same analysis framework, it study the certainty and uncertainty of the target for engineering issues from three measurement directions about identity, difference and opposition. In the end, it further establish the relationship between measurement directions. At present, many experts and scholars have applied set pair analysis theory to power grid planning. Under the research background of an engineering problem G, a set pair D is composed of two related sets, which is defined as D=(A, B). The engineering characteristics of the unit whose set belongs are discussed and subdivided into T characteristics. Among the T characteristics, set A and set B both contain X characteristics, and set A and set B are independent of each other in Z characteristics and only one set owns them, while the rest belong to the characteristics that set A and set B do not have. In conclusion, in the context of engineering problem G, the correlation function is:

$$u(A,B)=a+bi+cj \tag{1}$$

In formula(1):u(A, B) is the degree of connection between two related sets: A and B, and the value range of u(A, B) is [-1, 1]. In this section, the average value takes method of the different coefficient of the set pair analysis theory, which is combined in the establishment of the equipment-risk assessment model. Because the proportional value is more accurate for the assessment results in the hierarchical process of the connection degree, that is, i is divided into a certain range according to a certain proportion. In this paper, i is divided in an equal proportion way according to the equipment maintenance strategy. We correspond a, b and c respectively into the degree of identity, difference and opposition of engineering problem G, where a=X/T, b=Z/T, c=(T-X-Z)/T;I is the difference coefficient, and generally i is between [-1, 1]; When j is the coefficient of opposites, j is usually taken as -1.

The linkage degree expression in formula (1) divides the precision into three levels, which is called ternary linkage degree. In the application of many engineering problems, the ternary relation degree has sufficient accuracy, but for other systems (fault diagnosis of power equipment) that require high-precision evaluation values[13], such accuracy still cannot meet the requirements. Therefore, according to the extensibility of set pair analysis, we have made scalability for b in the linkage degree function (1). According to the actual situation, b is set up according to specific levels, and relevant scientific research experts name the expanded connection degree function as the multivariate connection degree function, as shown in formula (2):

$$u=a+b_1i_1+b_2i_2+...+b_{l-2}i_{l-2}+cj \tag{2}$$

In this section, formula(2) is named as the L-element connection degree function, R=[a, b_1, . . . , b_{L-2}, c] is named as the same-difference inverse evaluation matrix, and E=[1, i_1, . . . , i_{L-2}, j] is named as the same-difference inverse coefficient matrix.

Association rule technology is a kind of data mining theory, which was first used to study the habit correlation of customer's purchase behavior at this early stage. This method can be used to study the correlation between different items in the same event. The data representing various indicators provide a favorable data basis for transformer condition assessment. These data bases which have polymorphism characteristics are often heterogeneous. Then, how to mine the standard data that can effectively and comprehensively express the equipment operation status from the above massive information assessment system is the prerequisite for the research of equipment risk assessment.

The status of transformer can be classified as normal, attention, minor, abnormal, serious, etc.

Its status is related to the fault type of equipment. The damage degree of fault type to equipment is calculated from the support and confidence of historical data. This chapter divides the fault type into nine states, and the fault type can be calculated from 24 fault symptoms. In the judgment of fault type, the corresponding fault symptoms are taken according to the support degree and it is evaluated according to the rules of the same difference opposite evaluation matrix.

According to the related concepts of association rules, this paper defines association rules as follows:

Definition 1:If an association rule set is *D*, it is named as a transaction database, and the database *D* contains *N*-subset transactions, then the association rule set *D* can be defined as: *D*={*d*1, *d*2, . . . , *d*N}, and *d* is a subset of the association rule set.

Definition 2: In subset d, each subset consists of multiple events. At this time, subset *d* can be defined as:d={ ψ_1, ψ_2, ⋯, ψ_M}, there are *M* transaction items in the subset. Therefore, there are a total of *L* transaction items in association rule set *D*, The set of transaction items contained in association rule set *D* is:d={ ψ_1, ψ_2, ⋯, ψ_L}。

Definition 3: We define the set containing *k* transaction items as d_k subset, and name it *k* itemset, and then define the frequency of k-itemset in transaction database as $f(d_k)$. The proportion of $f(d_k)$ in transaction of database which are from *N* subsets is called the support degree of k itemset, as shown in Formula (3):

$$support\left(d_k\right)=P(d_k)=\frac{f(d_k)}{f(D)} \tag{3}$$

In this paper, we define the minimum support as $support_{\min}$, and we use this as a screening basis to obtain a k-item set that is greater than the minimum support[14].

Definition 4: Association rules are represented by A and B, which are transaction subsets. $A \in d=\{\psi_1, \psi_2, \cdots, \psi_L\}$, $B \in d=\{\psi_1, \psi_2, \cdots, \psi_L\}$, $A \cap B$ is an empty set, and defines A as the premise. If B is the subsequent conclusion, so it can represent $A \rightarrow B$.

Definition 5: $A \cup B$ is defined as a transaction set containing transaction subsets A and B. On the basis of definition 4, the probability when association rule set D contains transaction subset A, which define it as $confidence(A \rightarrow B)$, as shown in formula (4):

$$confidence(A \rightarrow B)=P(B|A)=\frac{f(A \cup B)}{f(A)} \tag{4}$$

In association rules, support and confidence represent the validity and certainty of the related transaction set respectively. When the support of k-item set in definition 3 is higher, it represents the closer correlation between the front and back items. The higher the confidence level between transaction A-subsets and B-subsets in definition 5, the more stable the relationship between transaction subsets.

There are many types of faults in transformers, it is difficult for a certain classification method to classify types. This article is mainly based on the "Guide for condition evaluation of Oil -immersed power transformers (reactors)", it is based on actual operating experience referring to the fault classification set in previous experience, the common fault types of transformers are finally divided into 9 types, as shown in Table 1 and Table 2.

It can be roughly divided into winding fault, core fault, current circuit overheating, etc. According to the insulation characteristics of equipment, faults can be divided into insulation damp, arc discharge, insulation aging, insulation oil deterioration, etc; According to the circuit fault, the fault can be divided into partial discharge and oil flow discharge. The above fault types are shown in Table 1:

Table 1. Types of faults in power transformers

Fault item	Fault type	Fault item	Fault type
F_1	Winding fault	F_6	Insulation aging
F_2	Core failure	F_7	Deterioration of insulating oil
F_3	Current circuitoverheating	F_8	partial discharge
F_4	Insulation damped	F_9	Oil flow discharge
F_5	Arc discharge		

In this chapter, the complex logic relationship is established according to the state information in the power system, and then the transformer fault is evaluated. However, some state information cannot be simply analyzed quantitatively, which brings certain challenges to the evaluation of transformers in this chapter. Although the amount of monitoring data collected is large, the value density is low. Therefore, it is necessary to select the most representative fault symptoms of transformers as specific indicators to evaluate the health of transformers.

The state information of power transformers is numerous. If all state information is considered, the fault diagnosis system will be extremely complex, and some state information is relatively vague and not suitable for quantitative description, which is not conducive for a evaluation of transformers to be comprehensive and accurate. To verify the correctness and effectiveness of the method proposed in this article, a 220kV oil-filled transformer(SFPS9-180000/220) was analyzed as a case in a substation where in Liaoning Province.

By reviewing the relevant information of this transformer [15], it was found that both the initial values of the 24 state variables in Table 2 exist. Therefore, these 24 state variables can be selected as fault symptoms for this diagnosis. The relevant data of fault symptoms are shown in Table 5. The Liaoning Electric Power Research Institute provided 1238 sets of historical test data from transformers with similar operating environments. These known fault types from tested transformers are specific. The results after sorting are shown in Table A.

According to the Inspection Specifications for On-line Monitoring Device of Substation Equipment, the device of Transformer Core Grounding Current and other relevant regulations in the Test Procedures for Condition are based on Maintenance of Power Transmission and Transformation Equipment issued by the State Grid in January 2014 [16], the fault characteristics closely related to the fault state item set and with a quantitative process are selected, as shown in Table 2:

Table 2. Fault characteristics of power transformers

Symptom set	Characteristic analysis	Symptom set	Characteristic analysis
S_1	Transformer insulation oil loss	S_{13}	Relative gas production(CO)
S_2	Water content in oil	S_{14}	Relative gas production(CO_2)
S_3	Dielectric oil breakdown voltage	S_{15}	Short-circuit impedance difference
S_4	Absorptance	S_{16}	Dielectric loss (Winding insulation)
S_5	Polarization index	S_{17}	Initial difference(capacitance value)
S_6	Volume resistivity	S_{18}	The content of C_2H_2
S_7	The content of H_2	S_{19}	Partial discharge
S_8	Core grounding current	S_{20}	Gas content in oil
S_9	Insulation resistance of iron core	S_{21}	The content of CH_4
S_{10}	The content of C_2H_6	S_{22}	Oil static current(neutral point)
S_{11}	The content of C_2H_4	S_{23}	The content of furfural
S_{12}	Difference of phase-phase resistance	S_{24}	Degree of polymerization

As shown in Table 2, according to the electrical test of the transformer, the following indicators can be quantified:insulation resistance absorption ratio, polarization index, volume resistivity and other 11 characteristic indicators. it quantifies the following indexes according to oil chromatographic analysis: 7 characteristic indexes such as H_2 content, C_2H_6 content and C_2H_4 content. According to the insulating oil test, the following indexes are quantified:dielectric loss of insulating oil, water content in oil, breakdown voltage of oil, etc. Finally, the structural characteristics are quantified according to the physical properties of the materials, and the quantitative index is the degree of polymerization of the paperboard.

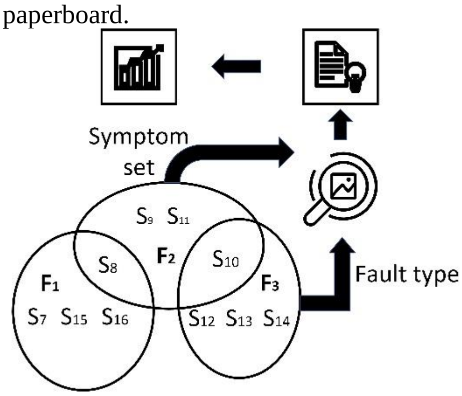

Fig. 2. Correlation between Symptom set and Fault type

This article extracts 9 types of power transformer faults [17], and it also select 24 types of transformer variables of monitoring state as symptom values. The symptom quantities contained in the fault types have a cross relationship, as shown in Figure 2.

The evaluation values of each fault state of power transformers vary in dimension level. If the data is not processed in a standardized form, it will lead to big data devouring small data. Therefore, this paper introduces the relative degree to quantify the data in a standardized way, so that the data of weak dimensions also show the same importance. This section combined with the characteristics of power data acquisition is based on the relative deterioration degree, The normalized treatment method of fault symptoms is introduced, as shown in Formula (5):

$$x_n = \frac{z' - z_n}{z' - z_f} \tag{5}$$

As shown in Table 3, this section introduces the corresponding connection function according to the relative deterioration of the transformer [18]. In this paper, traditional power equipment is generally summarized as qualified or unqualified. This paper subdivides the equipment into five states according to the degree of loss: normal, attention, slight, abnormal and serious.

Table 3. Relative degradation degree of transformer condition assessment

running state	normal	attention	slight	abnormal	serious
deteriorative degree	0. 8~1	0. 6~0. 8	0. 4~0. 6	0. 2~0. 4	0~0. 2
Connection	0. 6~1	0. 2~0. 6	0. 2~-0. 2	-0. 2~-0. 6	-0. 6~-1

The fault symptom is defined as $S_{m,n}$, which represent that a fault symptom-n is from fault type m. According to formula (3. 5), the relative deterioration degree of each fault symptom is substituted into the corresponding formula to obtain the corresponding correlation degree values of each fault symptom under five status levels as $r_1(S_{m,n})$, $r_2(S_{m,n})$, $r_3(S_{m,n})$, $r_4(S_{m,n})$, $r_5(S_{m,n})$.

The expression of Similarity Difference Inverse Evaluation Matrix of $S_{m,n}$ of fault symptom is Formula (6):

$$R_{m,n} = [r_1(S_{m,n}), r_2(S_{m,n}), r_3(S_{m,n}), r_4(S_{m,n}), r_5(S_{m,n})] \tag{6}$$

To sum up, the same-different and opposite evaluation matrix of fault type can be expressed by formula (7):

$$R_m' = [w_{m,1}, w_{m,2}, ..., w_{m,N_m}] \begin{bmatrix} R_{m,1} \\ R_{m,2} \\ ... \\ R_{m,N_m} \end{bmatrix} \tag{7}$$

Combining set pair analysis theory and IDR evaluation matrix, the fault diagnosis process of transformer is constructed as shown in Figure 3, and the work steps are as follows:

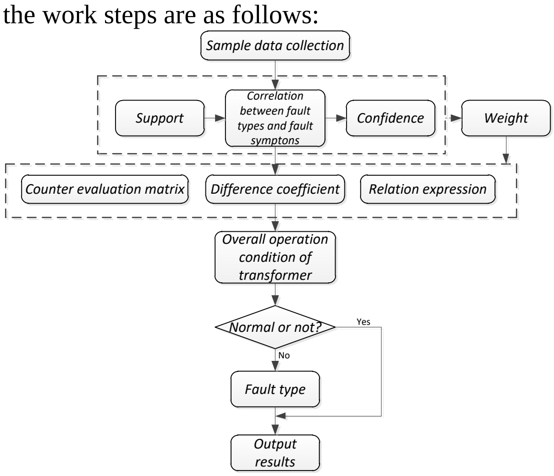

Fig. 3. Transformer fault diagnosis method based on spatial factor weight theory

Combining set pair analysis theory and IDR evaluation matrix, the fault diagnosis process of transformer is constructed as shown in Figure 3. The work steps are as follows:

1. According to the association rule theory, the historical fault data of transformers in actual operation are classified into fault types and fault symptom sets. We establish nine typical fault types were shown in Table 1 and 24 typical fault symptoms were shown in Table 2.
2. The measurement information of each part of the power transformer is collected according to step1. Finally we obtain the relative deterioration degree and score value of the fault type according to confidence formula(4) and relative deterioration formula(5),
3. It collect the calculation information of the fault symptoms under the operation state of the transformer. Then, it determine the number of element from the contact degree function according to the transformer fault state evaluation information in Table 3.

4. The correlation coefficient of each fault type of the transformer and the overall operation condition of the equipment were determined according to the theory of contact degree, the formula of the same different opposite evaluation matrix of fault symptoms (6), and the same different opposite evaluation matrix of fault types (7). The process is shown in Figure 4.
5. Refer to Table 3, it determine whether the equipment operates normally according to the output results. Otherwise, it determine the status information and fault type of the equipment according to the specific coefficient and the diagnosis results.

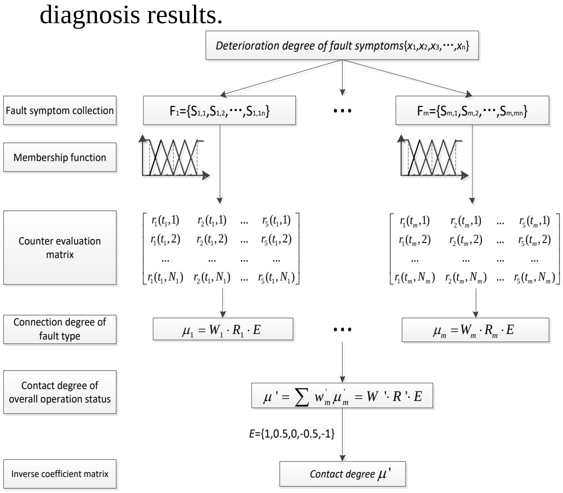

Fig. 4. The basic framework of the application of similarity, difference and counter evaluation
Health

3. EXAMPLE ANALYSIS BASED ON EVALUATION MODEL

This section collects the historical data of faults, and it counts the times of exceeding the standard of historical data and fault cases [19]. The times of exceeding the standard refer to the times of single symptom set in any state of the equipment. As for the support factor, the basic screening with 70%-support are described above(the symptoms related to the fault are included in the fault cases). In Appendix, the positions before the separator "/" represent the times of exceeding the standard and the positions after the separator "/" represent the degree of support respectively. According to the fault symptom collection data in Table A, we take the constant weight calculation process of fault case F_1 as an example, and then extending to other fault types, it first calculate the fault case F_1 according to the support formula (3) of the times of exceeding the standard. The process steps are as follows:

1. This paper counts the number of winding faults as 143, and it counts the number of cases where the fault symptom exceeds the standard when the winding fault occurs. According to Table 2, in the winding fault, the possible abnormal fault symptoms include:water content in oil, oil breakdown voltage, insulation resistance absorption ratio, volume resistivity, H_2 content, core grounding current, C_2H_6 content, C_2H_4 content, initial value difference of winding short-circuit impedance, winding insulation dielectric loss Initial value difference of winding capacitance. The exceeding standard process of the above fault symptoms is recorded as:

$f(S_{1,2}、F_1)= 5$、$f(S_{1,3}、F_1)= 1$、$f(S_{1,4}、F_1)= 2$、$f(S_{1,6}、F_1)= 2$、$f(S_{1,7}、F_1)= 120$、$f(S_{1,8}、F_1)= 130$、$f(S_{1,10}、F_1)= 5$、$f(S_{1,15}、F_1)= 126$、$f(S_{1,16}、F_1)= 121$、$f(S_{1,17}、F_1)= 56$。

2. According to the support formula (3), this paper calculates the fault symptom support in the first step:

$Support(S_{1,2} \rightarrow F_1) = P(S_{1,2} \cup F_1) = f(S_{1,2} \cup F_1)*100\%/D_{F1}=5*100\%/140=3.57\%$;
$Support(S_{1,3} \rightarrow F_1) = P(S_{1,3} \cup F_1) = f(S_{1,3} \cup F_1)*100\%/D_{F1}=1*100\%/140=0.71\%$;
$Support(S_{1,4} \rightarrow F_1) = P(S_{1,4} \cup F_1) = f(S_{1,4} \cup F_1)*100\%/D_{F1}=2*100\%/140=1.43\%$;
$Support(S_{1,6} \rightarrow F_1) = P(S_{1,6} \cup F_1) = f(S_{1,6} \cup F_1)*100\%/D_{F1}=2*100\%/140=1.43\%$;
$Support(S_{1,7} \rightarrow F_1) = P(S_{1,7} \cup F_1) = f(S_{1,7} \cup F_1)*100\%/D_{F1}=120*100\%/140=85.71\%$;
$Support(S_{1,8} \rightarrow F_1) = P(S_{1,8} \cup F_1) = f(S_{1,8} \cup F_1)*100\%/D_{F1}=130*100\%/140=92.86\%$;
$Support(S_{1,10} \rightarrow F_1) = P(S_{1,10} \cup F_1) = f(S_{1,10} \cup F_1)*100\%/D_{F1}=5*100\%/140=3.57\%$;
$Support(S_{1,15} \rightarrow F_1) = P(S_{1,15} \cup F_1) = f(S_{1,15} \cup F_1)*100\%/D_{F1}=126*100\%/140=90.00\%$;
$Support(S_{1,16} \rightarrow F_1) = P(S_{1,16} \cup F_1) = f(S_{1,16} \cup F_1)*100\%/D_{F1}=121*100\%/140=86.43\%$;
$Support(S_{1,17} \rightarrow F_1) = P(S_{1,17} \cup F_1) = f(S_{1,17} \cup F_1)*100\%/D_{F1}=56*100\%/140=40.00\%$。

According to the above setting of 70% of the support threshold, the groups S_7, S_8, S_{15} and S_{16} with the highest correlation of the fault cases will be selected.

3. The paper Supplement the previous step, we calculate and screen according to the support degree of formula (3) to obtain the four groups that calculated in this step. Then, we obtain the confidence degree of fault symptoms according to formula(4). The calculation process is as follows:

$C_{1,1}=confidence(S_{1,7} \rightarrow F_1) = P(F_1 | S_{1,7}) = f(F_1 \cup S_{1,7}) / f(S_{1,7})=120/433=27.71\%$;
$C_{1,2}=confidence(S_{1,8} \rightarrow F_1) = P(F_1 | S_{1,8}) = f(F_1 \cup S_{1,8}) / f(S_{1,8})=130/282=46.10\%$
$C_{1,3}=confidence(S_{1,15} \rightarrow F_1) = P(F_1 | S_{1,15}) = f(F_1 \cup S_{1,15}) / f(S_{1,15})=126/134=94.03\%$;
$C_{1,4}=confidence(S_{1,16} \rightarrow F_1) = P(F_1 | S_{1,16}) = f(F_1 \cup S_{1,16}) / f(S_{1,16})=121/273=44.32\%$。

4. Next, we calculate the constant weight of the four symptom sets by using the constant weight calculation formula. The calculation process is as follows:

$w_{1,1}$= 27. 71/(27. 71+46. 10+94. 03+44. 32)=0. 1306 ;

$w_{1,2}$= 46. 10/(27. 71+46. 10+94. 03+44. 32)=0. 2173 ;

$w_{1,3}$= 94. 03/(27. 71+46. 10+94. 03+44. 32)=0. 4432；

$w_{1,4}$= 44. 32/(27. 71+46. 10+94. 03+44. 32)=0. 2089。

Referring to the calculation process of F_1 (constant weight coefficient), we calculated the constant weight coefficient of each fault type, and the integrated results are shown in Table B from appendix. According to Table 4, the fault types are divided into: winding fault, core fault, current circuit overheating, insulation moisture, arc discharge, insulation aging, insulation oil degradation, partial discharge, oil flow discharge. The physical morphology and chemical reaction corresponding to the fault type are composed of 24 fault symptoms, which are in a cross form. The same fault symptoms may correspond to multiple fault types. The paper takes the arc discharge fault type as an example, the fault symptoms include H_2-content, winding DC resistance difference, C_2H_2 content, and partial discharge, and these are based on the calculation of the analysis theory of the association rule set. The constant weight coefficients are 0. 2102, 0. 2579, 0. 2794 and 0. 2525 respectively.

In this paper, the collected information of a 220kV transformer in a 220kVsubstation in a city is taken as an example for checking calculation. According to the standard processing of fault symptoms whose test data is shown in Table 5 in this paper. The table contains the standard value, initial value and measured value of 24 groups of fault symptoms, and the standard value is often defined as the attention value in the project, which means that when the measured value is close to the standard value, the fault symptom may show abnormalities.

In addition, Table 5 shows the abnormal status of the real-time test data of power transformer on several fault symptoms which including H_2 content, core grounding current, initial value difference of winding short-circuit impedance, and winding insulation dielectric loss. The standard value of H_2 content is 150uL/L, but the measured value is 142uL/L; The standard value of iron core grounding current is 0. 1A, but the actual measured value is 0. 29A that has seriously exceeded the standard. The standard value of the initial value difference of the winding short-circuit impedance is 3%, but the actual measured value is 4. 5% that at position of attention. The standard value of winding insulation dielectric loss is 0. 8%, but the measured value is 1. 0%.

According to the relative deterioration formula (5), the reference standard value, test value and initial value in Table 5 are substituted to obtain the relative deterioration of the fault symptoms of the 220kV power transformer. The results are shown in Table 6, the relative deterioration of each fault feature is collected. According to the relative deterioration of the measured and standardized fault symptoms at this time, the evaluation logic of the first fault type about "winding fault", actually, it is analyzed and elaborated based on the calculation of the IDR evaluation matrix. Firstly, the IDR evaluation matrix of the equipment fault type is calculated. According to the calculation method of this fault type, the fault type relation degree equation of other fault types is obtained, and then it is also based on the variable weight coefficient. The identity difference inverse evaluation matrix about the operation state of power equipment is carried out in the end.

Table 5. Test data of fault symptom of power transformer

Fault symptoms	Standard value	Initial value	Measured value
S_1	4%	0. 5%	1. 6%
S_2	25mg/L	3. 5mg/L	9. 5mg/L
S_3	35KV	58KV	52KV
S_4	1. 3	2	1. 59
S_5	1. 5	2. 5	2. 01
S_6	$5*10^9$Ω•m	$60*10^9$Ω•m	$51*10^9$Ω•m
S_7	150 u L/L	6. 1 u L/L	142 u L/L
S_8	0. 1A	0. 01A	0. 29A
S_9	100MΩ	1000MΩ	1000MΩ
S_{10}	65 u L/L	2. 3 u L/L	3. 5 u L/L
S_{11}	50 u L/L	4. 8 u L/L	7. 2 u L/L
S_{12}	4%	1%	1. 2%
S_{13}	100%/月	0	11%/月
S_{14}	200%/月	0	15%/月
S_{15}	3%	1%	4. 5%
S_{16}	0. 8%	0. 17%	1. 0%
S_{17}	5%	1%	1. 2%
S_{18}	5 u L/L	0	0
S_{19}	500pC	30pC	69pC
S_{20}	3%	1%	1. 2%
S_{21}	100 u L/L	8. 7 u L/L	18. 2 u L/L
S_{22}	1 u A	0. 02 u A	0. 03 u A
S_{23}	0. 2mg/L	0mg/L	0. 01mg/L
S_{24}	250	1000	950

Table 6. Relative degradation degree of power transformer fault symptoms

Fault symptoms	Relative deterioration	Fault symptoms	Relative deterioration
S_1	0. 7660	S_{13}	0. 9154
S_2	0. 7931	S_{14}	0. 9423
S_3	0. 8069	S_{15}	0. 0000
S_4	0. 5900	S_{16}	0. 0460
S_5	0. 6360	S_{17}	0. 9636
S_6	0. 8397	S_{18}	1. 0000
S_7	0. 2806	S_{19}	0. 9371
S_8	0. 3333	S_{20}	0. 8966
S_9	1. 0000	S_{21}	0. 9217
S_{10}	0. 9854	S_{22}	0. 9922
S_{11}	0. 9601	S_{23}	0. 9615
S_{12}	0. 9524	S_{24}	0. 9381

Refer to Table 4 for constant weight coefficient of fault symptom, W1=[0. 1306, 0. 2173, 0. 4432, 0. 2089], and according to the connection degree formula (7), the connection degree equation of winding fault is obtained as follows:

$$u_1 = W_1 \cdot R_1 \cdot E = \begin{bmatrix}0.1306, & 0.2173, & 0.4432, & 0.2089\end{bmatrix} \begin{bmatrix} 0 & 0 & 0 & 0.903 & 0.097 \\ 0 & 0 & 0.165 & 0.835 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ i_1 \\ i_2 \\ i_3 \\ j \end{bmatrix}$$

$$=0+0i+0.0359i+0.2994i+0.6612j$$

The expression form of the connection degree equation for this fault type is based on five reference quantities, and each value is assigned according to the equipartition method in the set pair analysis theory. In this chapter, i_1, i_2, i_3, and j are assigned [-0. 5, 0, 0. 5, 1] respectively, and their calculation results will be described in detail in the subsequent steps.

According to the above method, this paper firstly constructs the relative deterioration degree of the fault characteristics corresponding to each fault type, and then we make the relative deterioration degree matrix. Finally, it is constructed according to the constant weight coefficient of each fault type, and it calculate the similarity difference inverse evaluation correlation equation of the remaining eight fault types:

$$u_2 = 0.7005 + 0i_1 + 0.0494i_2 + 0.25i_3 + 0j;$$
$$u_3 = 1.0000 + 0i_1 + 0i_2 + 0i_3 + 0j;$$
$$u_4 = 0.1816 + 0.4552i_1 + 0.2192i_2 + 0.0631i_3 + 0.0068j;$$
$$u_5 = 0.7898 + 0i_1 + 0i_2 + 0.1898i_3 + 0.0204j;$$
$$u_6 = 0.6796 + 0.1047i_1 + 0i_2 + 0i_3 + 0.2157j;$$
$$u_7 = 0.6959 + 0.3040i_1 + 0i_2 + 0i_3 + 0j;$$
$$u_8 = 0.8204 + 0.1796i_1 + 0i_2 + 0i_3 + 0j;$$
$$u_9 = 0.8468 + 0.1533i_1 + 0i_2 + 0i_3 + 0j;$$

Wherein it is combined into a new IDR evaluation matrix which the IDR evaluation process of 9 fault types are:

$$R' = \begin{bmatrix} 0 & 0 & 0.0359 & 0.2994 & 0.6612 \\ 0.7005 & 0 & 0.0494 & 0.25 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0.1816 & 0.4552 & 0.2192 & 0.0631 & 0.0068 \\ 0.7898 & 0 & 0 & 0.1898 & 0.0204 \\ 0.6796 & 0.1047 & 0 & 0 & 0.2157 \\ 0.6959 & 0.3040 & 0 & 0 & 0 \\ 0.8204 & 0.1796 & 0 & 0 & 0 \\ 0.8468 & 0.1533 & 0 & 0 & 0 \end{bmatrix}$$

Based on the relative deterioration after standardized treatment in Table 5 and Table 6, according to the scoring formula (7) of the fault type, the constant weight coefficient converted in Table 4 is substituted to obtain the calculation information of the power transformer fault type. With the help of the scoring value of each fault type, the variable weight coefficient of each fault type is calculated. The results are shown in Table 7.

Table 7. Calculation information of fault type of power transformer

Fault type	Scoring value y_m	Variable weight coefficient w_m’
F_1	11. 87	0. 4631
F_2	78. 92	0. 0697
F_3	94. 17	0. 0584
F_4	68. 54	0. 0802
F_5	82. 06	0. 0670
F_6	71. 54	0. 0768
F_7	86. 83	0. 0633
F_8	90. 76	0. 0606
F_9	90. 35	0. 0608

Refer to the variable weight coefficient of each fault type in Table 7, and it calculate the overall health status of the transformer according to Formula (7). The calculation process of the contact function is as follows:

$$u = W \cdot R' \cdot E = \begin{bmatrix} 0.4631 \\ 0.0697 \\ 0.0584 \\ 0.0802 \\ 0.0670 \\ 0.0768 \\ 0.0633 \\ 0.0606 \\ 0.0608 \end{bmatrix}^T \begin{bmatrix} 0 & 0 & 0.0359 & 0.2994 & 0.6612 \\ 0.7005 & 0 & 0.0494 & 0.25 & 0 \\ 1.0000 & 0 & 0 & 0 & 0 \\ 0.1816 & 0.4552 & 0.2192 & 0.0631 & 0.0068 \\ 0.7898 & 0 & 0 & 0.1898 & 0.0204 \\ 0.6796 & 0.1047 & 0 & 0 & 0.2157 \\ 0.6959 & 0.3040 & 0 & 0 & 0 \\ 0.8204 & 0.1796 & 0 & 0 & 0 \\ 0.8468 & 0.1533 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ i_1 \\ i_2 \\ i_3 \\ j \end{bmatrix}$$
$$= 0.3726 + 0.0840i_1 + 0.0376i_2 + 0.1739i_3 + 0.3247j$$

During the operation of the power grid, the occurrence of any fault in the equipment is random and uncertain. Therefore, it is common for multiple equipment to be in an abnormal operating state, so them require maintenance/repair. However, the amount of resources allocated by enterprises is limited [18]. According to the research ideas in this article, the fault state can be quantified as a score between 0 and 1. The lower the score, the higher the probability of the fault occurrence and the higher the urgency of maintenance. Based on the different degradation stages of fault stages, this article divides the maintenance work of all faults into three priority levels, as shown in Figure 5 [20].

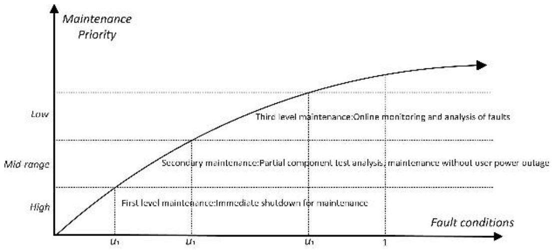

Fig. 5. Prioritization of Power Equipment Maintenance

In this paper, the values of [i_1, i_2, i_3, j] are respectively assigned as 0. 5, 0, -0. 5 and -1 by the equal division method, then $E=[1, 0.5, 0, -0.5, -1]^T$, so the value of u is 0. 0030. At this time, the transformer is in the priority arrangement state referring to Table 3. When the transformer is under maintenance, the personnel maintenance shall use the same difference-opposite evaluation contacting degree equation. These data are described above to calculate the contact degree equation of 9 fault types in the process of the fault location. The process is as follows:

$$u_1 = 0 + 0\times 0.5 + 0.0359\times 0 + 0.2994\times(-0.5) + 0.6612\times(-1) = -0.8109;$$
$$u_2 = 0.7005 + 0\times 0.5 + 0.0494\times 0 + 0.25\times(-0.5) + 0\times(-1) = 05755;$$
$$u_3 = 1.0000 + 0\times 0.5 + 0\times 0 + 0\times(-0.5) + 0\times(-1) = 1;$$
$$u_4 = 0.1816 + 0.4552\times 0.5 + 0.2192\times 0 + 0.0631\times(-0.5) + 0.0068\times(-1) = 0.3709;$$
$$u_5 = 0.7898 + 0\times 0.5 + 0\times 0 + 0.1898\times(-0.5) + 0.0204\times(-1) = 0.6745;$$
$$u_6 = 0.6796 + 0.1047\times 0.5 + 0\times 0 + 0\times(-0.5) + 0.2157\times(-1) = 0.5163;$$
$$u_7 = 0.6959 + 0.3040\times 0.5 + 0\times 0 + 0\times(-0.5) + 0\times(-1) = 0.8479;$$
$$u_8 = 0.8204 + 0.1796\times 0.5 + 0\times 0 + 0\times(-0.5) + 0\times(-1) = 0.9102;$$
$$u_9 = 0.8468 + 0.1533\times 0.5 + 0\times 0 + 0\times(-0.5) + 0\times(-1) = 0.9235;$$

As shown in Figure 6, the method calculates the overall rating value of the transformer based on its variable weight coefficient and comprehensive rating value [21]. By comparing with these failure type in the equipment condition maintenance, the overall rating value calculated by this method could determine the scope and severity of transformer faults, then we provide corresponding maintenance opinions.

Therefore, through the comparison of the fault type correlation value, the winding fault is -0. 8109, which is the lowest in the whole group. Therefore, it is speculated that the possibility of winding fault is greater than other fault types, so the personnel maintenance can focus on the winding fault.

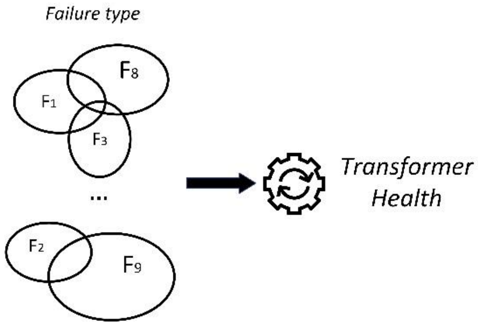

Fig. 6. Correlation between Failure type and Transformer

4. CONCLUSION

The current detection and monitoring methods for power equipment in power grids are complex, and the analysis of a large amount of data obtained from operational detection is crucial for the state assessment and fault diagnosis in the power grid. The following conclusions can be drawn from this study:

1. The association rules for monitoring data analysis of transformer fault types and fault symptoms is practical and effective. By calculating support and confidence, the coupling relationship and weight between fault types and fault symptoms could be obtained, which avoid the subjectivity of expert opinions or experience.
2. This article attempts to organically combine set pair analysis and association rules, and apply them to power transformer fault diagnosis, which has certain advantages in dealing with uncertain problems. The concept of fuzzy theoretical membership degree was introduced in the process of constructing a multiple evaluation matrix, which objectively reflects the corresponding relationship between state evaluation indicators and operational state.
3. Comparative analysis of examples show that the fusion and application of multiple data analysis achieve good state evaluation and get well diagnosis results, and it also perform well in handling multi fault problems. Moreover, the process of the algorithm in this paper is easy to program with computers, which has good operability and scalability.

Finally, the working state of the transformer is classified, and the associated fault symptoms are determined. In the quantification process of fault symptom set, the relative deterioration degree and membership degree are introduced, the evaluation matrix is constructed, and then the relationship matrix between fault symptom set and fault type is determined according to the factors in factor space. According to the division of the health level, the health status of the transformer is diagnosed. Finally, the accuracy and effectiveness of the method in this chapter are verified by an example.

Source of funding: This work is supported by Science Foundation of State Grid Fujian Electric Power Company(Grant, No. 52133121001F).

Author contributions: *research concept and design, S.W., D.C., Z.C., M.B., H.O. X.L.; Collection and/or assembly of data, S.W., H.O., W.H., C.C.; Data analysis and interpretation, S.W., D.C., Z.C., M.B., X.L.; Writing the article, S.W.; Critical revision of the article, Y.S.; Final approval of the article, S.W., D.C., Z.C., M.B., H.O., X.L., W.H., C.C., Y.S.;*

Declaration of competing interest: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

REFERENCES

1. Tang W, Niu Z, Zhao B. Research and application of data-driven artificial intelligence technology for condition analysis of power equipment. High Voltage Engineering 2020; 46(09): 2985-2999.
2. Chu J, Wang Q, Liu Y, Pan J, Yuan H, Yang A, Wang X, Rong M. Fault Diagnosis of SF6-Insulated Equipment by Micro Gas Sensor Array. IEEE Transactions on Power Delivery 2023; 38(01): 222-230.
3. Zhang S, Wang R, Wang L, Si Y, Lin A, Wang Y. Fault Diagnosis for Power Converters Based on Incremental Learning. IEEE Transactions on Instrumentation and Measurement 2023; 72: 1–13. https://doi.org/10.1109/TIM.2023.3265095.
4. Wang Y, Yan J, Yang Z, Qi Z, Wang J, Geng Y. Gas-Insulated Switchgear Insulation Defect Diagnosis via a Novel Domain Adaptive Graph Convolutional Network. IEEE Transactions on Instrumentation and Measurement 2022; 71: 1–10. https://doi.org/10.1109/TIM.2022.3160543.
5. Carvalho Fagundes MV, Cheles Keler Á, Oliveira Teles E, Vieira de Melo SAB, Mendonça Freires FG. Multicriteria Decision-Making System for Supplier Selection Considering Risk: A Computational Fuzzy AHP-Based Approach. IEEE Latin America Transactions 2021; 19(9): 1564–1572. https://doi.org/10.1109/TLA.2021.9468610.
6. Liu JB, Malik MA, Ayub N, H. Siddiqui MA. Distance measures for multiple-attributes decision-making based on connection numbers of set pair analysis with dual hesitant fuzzy sets. IEEE Access 2020; 8: 9172-9184. https://doi.org/10.1109/ACCESS.2019.2963484.
7. Rastogi SK, Shah SS, Singh BN, Bhattacharya S. Mode Analysis, Transformer Saturation, and Fault Diagnosis Technique for an Open-Circuit Fault in a Three-Phase DAB Converter. IEEE Transactions on Power Electronics 2023; 38(6): 7644–60. https://doi.org/10.1109/TPEL.2023.3241654.
8. Gao X, Pan L, Deng Y. Quantum Pythagorean Fuzzy Evidence Theory: A Negation of Quantum Mass Function View. IEEE Transactions on Fuzzy Systems 2022; 30(5): 1313–27. https://doi.org/10.1109/TFUZZ.2021.3057993.
9. Song SY, Wu F, Bai H, Wang HY. Evaluation of Reservoir Bank Landslide Susceptibility Degree Based on Interval Number and Set Pair Analysis Theory. Journal of Northeastern University (Natural Science) 2022; 43(2): 251-257.

10. Bazin A, Gros N, Bertaux A, Nicolle C. Condensed Representations of Association Rules in n-Ary Relations. IEEE Transactions on Knowledge and Data Engineering 2023; 35(5): 4598–607. https://doi.org/10.1109/TKDE.2022.3153709.
11. Grzejda R. Designation of a normal stiffness characteristic for a contact joint between elements fastened in a multi-bolted connection. Diagnostyka 2019; 15(2): 61–4.
12. Ziani D, Bendimerad E, Ayad A. Influence of the variety of steel tube materials on the impedance behavior of non-destructive eddy current testing. Diagnostyka. 2023;24(2):2023207. http://dx.doi.org/10.29354/diag/163092.
13. Zhang D. Fault diagnosis of ship power equipment based on adaptive neural network. International Journal of Emerging Electric Power Systems 2022; 23(6): 779–91. https://doi.org/10.1515/ijeeps-2022-0103.
14. Huang L, Song H, Wang Z, Li H, Ma D, Yu P. The Study of 2-D Magnetic Focusing Inversion Based on the Adjustable Exponential Minimum Spport Stabilizing Functional. IEEE Transactions on Geoscience and Remote Sensing 2023; 61: 1–10. https://doi.org/10.1109/TGRS.2023.3313201.
15. Khelafi A, Ibtiouen R, Djebli A, Touhami O. Design and modelling of three-to-five phase three-limbed transformer. IET Electric Power Applications 2023; 17(5): 670-686. https://doi.org/10.1049/elp2.12292.
16. Mingzhong P, Weiliang J, Ying J. On line monitoring device of bolt pressing force. 2020 7th International Forum on Electrical Engineering and Automation (IFEEA) 2020; 33-36.
17. Peng F, Gao H, Huang J, Guo Y, Liu Y, Zhang Y. Power Differential Protection for Transformer Based on Fault Component Network. IEEE Transactions on Power Delivery 2023; 38(4): 2464–77.
18. Wang F, Liang K, Zhong L, Sun Q, Chen S, Duan X, i in. On-Load Tap Changer Internal Contact Health Assessment Based on Ion Detection in Oil. IEEE Transactions on Dielectrics and Electrical Insulation 2023; 30(4): 1825–33. https://doi.org/10.1109/TDEI.2023.3248520.
19. Zhou H, Yin H, Zhao D, Cai L. Incremental Learning and Conditional Drift Adaptation for Nonstationary Industrial Process Fault Diagnosis. IEEE Transactions on Industrial Informatics 2023; 19(4): 5935–44. https://doi.org/10.1109/TII.2022.3179423.
20. Geng SJ, Wang XL. Predictive Maintenance Scheduling of Parallel Multiple Power Equipment Considering Fault State Deterioration. Systems Engineering 2023; 1-10. https://doi.org/10.1016/j.amc.2011.03.010.
21. Zhang S, Song H, Cai K. Multiobjective Optimization Design for Lightweight and Crash Safety of Body-in-White Based on Entropy Weighted Grey Relational Analysis and MNSGA-II. IEEE Acces 2022; 10: 67413-67436. https://doi.org/10.1109/ACCESS.2022.3185412.

Wang SHANYUAN (1994-), man,
Communication author, Master, Graduated from Northeastern University, Research on power grid operation and distribution electrical technology.
E-mail:wsyneu@163. com.
https://orcid. org/0009-0009-2465-5590

Cai DONGLIN (1992-), man, Master,
Graduated from Fuzhou University, Research on power electronics and power transmission.
E-mail:997417194@qq. com.
https://orcid. org/0009-0009-8650-0375

Chen ZHONGHONG(1995-), man,
Graduated from Fuzhou University, Research on Substation maintenance technology.
E-mail:270218440@qq. com.
https://orcid. org/0009-0002-2503-1105

Bai MENGLONG (1991-), man, Graduated from North China Electric Power University, Research on distribution electrical technology and power transmission.
E-mail:827047520@qq. com
https://orcid. org/0009-0008-6755-7619

Ouyang HONGYU (1995-), man,
Graduated from Fuzhou University, Research on Electrical automation and distribution electrical technology.
E-mail:512410224@qq. com
https://orcid. org/0009-0009-2885-2823

APPENDIX

Table A. Failure types and corresponding failure symptoms support

	Exceedance times of fault symptoms of fault type/support(%)									**Excede times**
	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	
S_1	0/0	0/0	0/0	121/96.03	5/3.31	138/92.62	121/93.08	101/87.83	115/92.00	601
S_2	5/3.57	0/0	0/0	120/95.24	1/0.66	1/0.67	100/76.92	104/90.43	2/1.60	333
S_3	1/0.71	0/0	0/0	119/94.44	3/1.99	0/0	98/75.38	3/2.61	0/0	224
S_4	2/1.43	0/0	0/0	116/92.06	0/0	3/2.01	2/1.54	0/0	0/0	123
S_5	0/0	0/0	0/0	100/79.37	3/1.99	4/2.68	3/2.31	1/0.87	1/0.8	112
S_6	2/1.43	0/0	0/0	99/78.57	0/0	131/87.92	112/86.15	4/3.48	119/95.20	467
S_7	120/85.71	6/3.75	2/1.41	111/88.10	126/83.44	3/2.01	3/2.31	61/53.04	1/0.8	433
S_8	130/92.86	151/94.38	0/0	0/0	0/0	0/0	1/0.77	0/0	0/0	282
S_9	0/0	149/93.13	0/0	100/79.37	0/0	6/4.03	112/86.15	1/0.87	0/0	368
S_{10}	5/3.57	139/86.88	106/74.65	0/0	0/0	2/1.34	0/0	0/0	0/0	252
S_{11}	0/0	121/75.63	65/45.77	3/2.38	3/1.99	4/2.68	5/3.85	102/88.70	106/84.80	409
S_{12}	0/0	0/0	130/91.55	0/0	130/86.09	3/2.01	2/2.31	96/83.48	2/1.60	364
S_{13}	0/0	11/6.88	131/92.25	0/0	0/0	2/1.34	4/3.08	3/2.61	0/0	151
S_{14}	0/0	0/0	126/88.73	0/0	0/0	5/3.36	5/3.85	1/0.87	0/0	137
S_{15}	126/90.00	1/0.63	0/0	0/0	0/0	6/4.03	1/0.77	0/0	0/0	134
S_{16}	121/86.43	2/1.25	0/0	0/0	2/1.32	138/92.62	7/5.38	0/0	3/2.40	273
S_{17}	56/40.00	3/1.88	0/0	1/0.79	1/0.66	2/1.34	0/0	0/0	0/0	63
S_{18}	0/0	2/1.25	0/0	2/1.59	142/94.04	0/0	0/0	105/91.30	116/92.80	367
S_{19}	0/0	1/0.63	0/0	0/0	129/85.43	131/87.92	3/2.31	102/88.70	3/2.40	369
S_{20}	0/0	0/0	0/0	16/12.70	3/1.99	138/92.62	62/47.69	1/0.87	121/96.80	341
S_{21}	0/0	0/0	0/0	8/6.35	0/0	3/2.01	5/3.85	3/2.61	0/0	19
S_{22}	0/0	0/0	0/0	3/2.38	1/0.66	0/0	3/2.31	0/0	1/0.8	8
S_{23}	0/0	0/0	0/0	3/2.38	2/1.32	142/95.30	99/76.15	4/3.48	0/0	250
S_{24}	0/0	0/0	0/0	2/1.59	0/0	61/40.94	0/0	1/0.87	2/1.60	66
Number Fault	140	160	142	126	151	149	130	115	125	

Table B. Classification function coefficients of fault types

Fault symptoms	Fault type								
	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9
S_1	13. 559	-5. 584	12. 763	66. 392	43. 644	44. 925	66. 822	56. 516	154. 221
S_2	114. 119	60. 066	-5. 949	212. 849	-15. 719	12. 479	146. 564	111. 839	-12. 703
S_3	132. 999	42. 043	12. 045	367. 515	-85. 914	-34. 167	247. 946	119. 067	-128. 597
S_4	87. 577	108. 790	20. 743	235. 045	35. 579	15. 202	152. 700	172. 067	111. 077
S_5	-15. 344	-82. 880	-70. 452	168. 618	-26. 875	-15. 202	-45. 020	-75. 496	-73. 006
S_6	-29. 368	-58. 584	6. 449	-72. 927	-0. 599	52. 235	-34. 210	-87. 695	15. 433
S_7	36. 596	-51. 816	9. 065	12. 915	-0. 030	2. 926	-17. 356	-7. 329	-32. 433
S_8	95. 205	652. 922	-64. 620	169. 766	-19. 248	1. 443	144. 094	111. 122	-13. 033
S_9	12. 651	194. 575	-29. 549	107. 912	-1. 048	-13. 150	111. 932	33. 928	-10. 751
S_{10}	51. 170	198. 984	10. 627	-2. 790	-6. 451	5. 032	4. 434	18. 917	11. 667
S_{11}	-26. 604	-6. 504	39. 994	-52. 144	6. 108	4. 878	-21. 659	-8. 856	10. 784
S_{12}	-27. 450	-1. 791	32. 197	-36. 239	61. 179	13. 634	-15. 110	35. 634	22. 522
S_{13}	34. 053	-37. 906	138. 836	54. 551	-35. 231	-28. 689	28. 277	-28. 630	-40. 276
S_{14}	-24. 441	-53. 507	142. 883	1. 080	-4. 884	20. 345	14. 054	14. 843	21. 420
S_{15}	624. 475	158. 603	-27. 606	314. 803	-31. 923	40. 094	191. 898	142. 771	-40. 780
S_{16}	169. 591	-1. 209	-4. 842	-12. 836	9. 542	8. 272	-8. 781	-15. 660	30. 372
S_{17}	141. 323	9. 175	-4. 551	26. 344	-1. 079	4. 230	19. 231	9. 933	5. 038
S_{18}	-0. 036	10. 201	-4. 243	7. 142	54. 596	8. 325	10. 203	2. 959	72. 462
S_{19}	-37. 674	18. 696	-7. 550	-53. 987	74. 900	11. 995	-9. 290	42. 964	53. 445
S_{20}	-27. 308	26. 638	2. 350	50. 353	26. 215	46. 536	77. 867	106. 118	57. 397
S_{21}	83. 060	81. 723	-9. 467	169. 998	-70. 471	-6. 380	115. 608	110. 503	-27. 914
S_{22}	5. 510	18. 100	-2. 379	-3. 235	-8. 828	-27. 133	-14. 652	1. 047	-19. 081
S_{23}	49. 245	9. 614	-12. 943	40. 257	-9. 501	170. 334	38. 192	54. 761	-64. 917
S_{24}	-135. 223	4. 059	4. 304	-27. 892	-26. 905	110. 0482	-42. 194	-45. 659	-52. 002
coefficient	-46320. 8	-47211. 3	-16332. 3	-49847. 1	-8465. 0	-20017. 2	-25730. 8	-18517. 1	-12838. 6