International Journal of Applied Mathematics in Control Engineering 5 (2022) 88-93

Contents lists available at YXpublications

International Journal of Applied Mathematics in Control Engineering

Journal homepage: http://www.ijamce.com

Fault Diagnosis of Power Transformer Based on Adaptive Principal Component Analysis

Wenxia Du[a], Yang Ning[b], Hailian Du[a,*], Tao Xin[a], Yanhong Wang[a]

[a] *Vocational and Technical College of Hebei Normal University, Shijiazhuang, Hebei 050024, China*

[b] *Electrical Engineering College of Northeast Electric Power University, Jilin, Jilin 132011, China*

ARTICLE INFO

Article history:
Received 10 March 2022
Accepted 14 May 2022
Available online 17 May 2022

Keywords:
Principal component analysis
Adaptive principal component analysis
Fault diagnosis
Power transformer

ABSTRACT

When the operation of power transformer is abnormal, the content of characteristic gas in transformer oil changes and has nonlinear and slow time-varying characteristics. In order to improve the accuracy of fault diagnosis, it is necessary to update the fault diagnosis model in real time. In this paper, the sliding window algorithm is used to continuously update the historical data. On this basis, the adaptive principal component model is established to obtain the self-adaptive updated SPE statistics and T^2 statistics control limits. The power transformer fault is monitored in real time. Finally, the fault type of the fault sample is judged according to the contribution rate of each variable. The simulation example shows that the fault diagnosis method based on adaptive principal component analysis can locate the fault more accurately and better adapt to the time-varying working conditions of power transformer.

1. Introduction

Power transformer is an important equipment of power system. Its stable and trouble free operation is the premise of safe and reliable operation of power system. When the transformer works abnormally, it is necessary to eliminate the fault in time and effectively. The faults of oil filled power transformer are mainly discharge fault and overheating fault (Tang Yongbo et al, 2010), the transformer oil can be sampled regularly for oil chromatogram analysis, and the abnormal condition of the power transformer can be judged according to the change of the content of dissolved characteristic gases (hydrogen, methane, ethane, ethylene and acetylene) in the oil.

With the development of science and technology, the automation of modern chemical plants is getting higher and higher, and the nonlinearity, time variability and uncertainty of variables in the system are more prominent, which poses a more serious challenge to the fault diagnosis technology. Principal component analysis theory is widely used in the field of fault diagnosis (Wen Daosong, 2011). For example, in the process of train operation, the working state monitoring of traction motor is the key to the stable and safe operation of the train. Using the principal component analysis method, the online state monitoring of traction equipment can be realized(Wei Jie, 2009); Principal component analysis (PCA) is applied to some problems of fault detection in boiler control process of thermal power plant(Zhu Kongwei, 2006; Huang Xiaobin et al, 2004; Huang Xiaobin et al, 2003). Tang Yongbo, Ou Yangwei and others proposed the application of principal component analysis in transformer fault detection and identification, and then proposed the method of reconstructing contribution to judge the type of transformer fault(Tang Yongbo et al, 2012).Because the change of characteristic gas content dissolved in oil has nonlinear and slow time-varying characteristics, the principal component model based on traditional principal component analysis can not better adapt to the time-varying characteristics of data. It is necessary to establish a real-time updated adaptive principal component model to improve the accuracy and effectiveness of transformer fault diagnosis.

At present, there are three types of adaptive principal component analysis. The first is to establish a PCA model to cover and cover all working modes as much as possible (Fang Ning, 2014). However, the collection of modeling data including all working conditions is very difficult. This method will become more conservative under the monitoring model, and the missed detection rate and false detection rate will be greatly improved. The second is to establish the model base through the identification of different working conditions and modes. Multi working condition PCA, this method focuses on identifying how the system switches to each other under different working conditions. In 2004, Huang Xiaobin and other scholars developed a new condition monitoring method for the

* Corresponding author.
E-mail addresses: duhailian@126.com (H. Du)
doi:

changing working conditions of thermal power plants: in order to distinguish different working conditions, key operating variables are used to further judge whether it is steady-state data according to the process data, and finally decide whether to carry out fault diagnosis according to the current real-time data (Huang Xiaobin et al, 2004). H. D. Jin et al. Used process knowledge to calculate and judge the reason for exceeding the limit of data statistics, whether it was due to switching working conditions or failure. Dae heehwang et al. Proposed a clustering analysis method to construct the monitoring method of "super" model. The third method is to update the model in real time under changing conditions, that is, adaptive principal component analysis. Weihua Li first proposed an adaptive PCA algorithm based on sliding window in. DoanX. On the basis of sliding window, Tien et al. Proposed to use the initial modeling data to calculate through the real-time update of normalized parameters and the collection and statistics of new sampling points. H. The robust recursive PCA method proposed by D. Jin et al in 2006 further improves the previous research. In addition, flaten et al. Proposed a "Caterpillar" algorithm based on two adjacent sliding window methods, which is used to detect the fluctuation of process data. Huang Xiaobin et al. Proposed a sliding window cumulative recursive method, and used this method to select the length of data suitable for establishing the model.

2. Adaptive principal component analysis

2.1 Principal component analysis fault diagnosis method

Principal component analysis (PCA) is an effective analysis method to transform multiple related variables into a few independent variables. Its advantage is to reduce the dimension of high-dimensional variable space under the principle of minimizing the loss of data information. The fault diagnosis steps of principal component analysis are as follows:

(1) Normalize each sample of the original data and form a matrix $X_{n\times m}$

$$X=\begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

n is the number of samples and m is the number of variables.

(2) Find covariance matrix S

$$S=\frac{1}{n-1}X^TX \tag{2}$$

(3) Eigenvalue of covariance matrix

According to the formula $Sp=\lambda p$, the eigenvalues of S matrix are obtained ($\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_m \ge 0$) and its corresponding eigenvector p_1 , p_2 ,…, p_m . p_i is orthogonal to each other, That is $p_i^Tp_i=1$, $p_i^Tp_j=0$, $(i\neq j)$, to form an eigenvalue eigenvector pair (λ_1,p_1), (λ_2,p_2),…, (λ_i,p_i),…, (λ_m,p_m).

(4) Number selection of principal components

The number of principal components L is determined according to the cumulative contribution rate of principal components greater than a certain value (cl, usually 85%)

$$\sum_{k=1}^{a} Contr(t_k)=\sum_{j=1}^{l}\lambda_j \,/\, \sum_{i=1}^{m}\lambda_i \ge cl \tag{3}$$

Where $Contr(t_k)$ represents the contribution rate of the k-th principal component.

$$Contr(t_k)=\lambda_k \,/\, \sum_{i=1}^{m}\lambda_i \tag{4}$$

(5) Calculate load matrix P

An eigenvalue decomposition of covariance matrix S is:

$$S=P\Lambda P^T=[\bar{P} \quad \tilde{P}]\Lambda[\bar{P} \quad \tilde{P}]^T \tag{5}$$

Where, the diagonal matrix $\Lambda=diag(\lambda_1\,\lambda_1\,\cdots\lambda_1)$ and satisfies $\lambda_1\ge\lambda_2\ge\cdots\ge\lambda_m$, $P=[\bar{P} \quad \tilde{P}]$ is called the load matrix, composed of eigenvector (load vector) $p_i\in R^m$, the first l columns of matrix P form matrix $\bar{P}$, and the remaining $m-l$ columns form matrix $\tilde{P}$.

(6) Calculate score matrix T

Let matrix X be decomposed into a linear combination of m variables, $X=t_1p_1^T+t_2p_2^T+\cdots+t_ip_i^T+\cdots+t_mp_m^T$ is called the score vector, also known as the principal element of X, and $T=[t_1,t_2,\cdots,t_i,\cdots,t_l,t_{l+1},\cdots,t_n]$ is the score matrix.

(7) T^2 and Q statistics calculation

In order to use the principal component model to monitor the production process, the control limit needs to be determined from the data of normal operation of the process, mainly including the square prediction error (SPE) control limit of the principal component model and the T^2 control limit of the score of the principal component model. When the SPE or score statistics of the principal component model exceed the control limit, it indicates that an abnormal situation has occurred in the process.

New sample x_{new} $(m\times 1)$ The calculation formula of Q statistics:

$$Q=x_{new}(I-\bar{P}\bar{P}^T){x_{new}}^T \tag{6}$$

SPE (Q Statistics) control limit calculation formula:

$$Q_\alpha=\theta_1\left[\frac{c_\alpha h_0\sqrt{2\theta_2}}{\theta_1}+1+\frac{\theta_2h_0(h_0-1)}{\theta_1^2}\right]^{\frac{1}{h_0}} \tag{7}$$

$$\theta_r=\sum_{j=l+1}^{m}\lambda_j^r(r=1,\ 2,\ 3) \tag{8}$$

$$h_0=1-\frac{2\theta_1\theta_3}{3\theta_2^2} \tag{9}$$

c_α is the confidence limit of the standard normal distribution, which meets the formula: $P\{N(0,1)>Nc_\alpha\,(0,1)\}=C_\alpha$, α takes about 0.01. If the system operates normally, the Q of the sample should meet $Q<Q_\alpha$. on the contrary, it can be considered that there is a fault.

For the new sample x_{new} $(m*1)$ (the new sample should be standardized by using the parameters standardized by the normal sample set), the calculation formula of T^2 statistic is as follows:

$$T^2=x_{new}\bar{P}\Lambda^{-1}\bar{P}^Tx_{new}^T \tag{10}$$

Calculation formula of T^2 control limit:

$$T_\alpha=\frac{a(n+1)(n-1)}{n(n-a)}F_\alpha(a,n-a) \tag{11}$$

α is the significance level, $1-\alpha$ is the confidence level, and $F_\alpha(a,n-a)$ is the F distribution. If the system operates normally, the sample T^2 value should meet $T^2<T_\alpha$, otherwise, it can be considered that there is a fault.

(8) Contribution rate diagram

Calculate the contribution rate of each variable x_j:

$$cont(i,j) = \frac{t_i^2}{\lambda_i} p(i,j)(x_j - u_j) \tag{12}$$

$p(i,j)$ is the (i,j)-th element of load matrix P, and u_j is the mean value of j variables.

Calculate the total contribution rate of process variable x_j:

$$CONTj = \sum_{i=1}^{r} cont(i,j) \tag{13}$$

Calculate the contribution rate of each variable to Q:

$$e = x^T(I - PP^T) \tag{14}$$

$$contq = e^2 \tag{15}$$

x is a new observation vector on the test set. According to the total contribution rate value, the priority of the variables causing the failure is distinguished. The equipment operator or engineer can immediately pay attention to the variables with high contribution rate value and judge the cause of out of control according to their process knowledge.

2.2 Adaptive principal component analysis

In view of the shortcomings of the transformer principal component model established by the transformer fault diagnosis method of principal component analysis, this chapter introduces the idea of sliding window to update the transformer principal component model, so that it can better adapt to the changes of working conditions and improve the effect of fault diagnosis.

2.2.1 Sliding window PCA algorithm

Because the current process state cannot be represented by the old historical data, the data of the principal component model needs to be updated in real time, and the sliding window PCA can replace the old historical data with new normal data, so it is suitable for slowly changing working conditions. The main principle is to set a sliding window with fixed length and let it slide forward with time to collect the sample matrix at time k, $X_k = (x_{k-L+1}, x_{k-L+2} \dots x_k)^T$, The sample matrix at time $k+1$ is $X_{k+1} = (x_{k-L+2}, x_{k-L+3} \dots x_{k+1})^T$, Replace the old data in X_k with the new data, then the common matrix of two adjacent samples is $\hat{X}_{k,k+1} = (x_{k-L+2}, x_{k-L+3} \dots x_k)^T$. The mean $\hat{b}_{k,k+1}$ and covariance $\hat{R}_{k,k+1}$ of the common matrix are(Fang Ning,2014):

$$\hat{b}_{k,k+1} = \frac{L}{L-1} b_k - \frac{1}{L-1} x_{k-L+1} \tag{16}$$

$$\hat{R}_{k,k+1} = \frac{L-1}{L-2}\left(R_k - \frac{1}{L-1} x_{k-L+1}^T x_{k-L+1} - \Sigma_k^{-1} \Delta \hat{b}_k \Delta \hat{b}_k^T \Sigma_k^{-1}\right) \tag{17}$$

$$\Delta \hat{b}_k = b_k - \Delta \hat{b}_{k,k+1} \tag{18}$$

The mean value of the sample data matrix at time k is b_k, and the covariance matrix of the sample data matrix at time k is R_k.

The mean value b_{k+1} and covariance R_{k+1} of the sample matrix at time $k+1$ are derived according to the mean value and covariance of the common matrix:

$$b_{k+1} = \frac{L-1}{L} \hat{b}_{k,k+1} + \frac{1}{L} x_{k+1} \tag{19}$$

$$R_{k+1} = \frac{L-2}{L-1}\left(\hat{R}_{k,k+1} + \frac{1}{L-1} x_{k+1}^T x_{k+1} + \Sigma_{k+1}^{-1} \Delta \hat{b}_{k+1} \Delta \hat{b}_{k+1}^T \Sigma_{k+1}^{-1}\right) \tag{20}$$

$$\Delta \hat{b}_{k+1} = b_{k+1} - \Delta \hat{b}_{k,k+1} \tag{21}$$

The mean value of the sample data matrix at time $k+1$ is b_{k+1}, and the covariance matrix of the sample data matrix at time $k+1$ is R_{k+1}.

According to the above calculation, finally calculate the covariance matrix of the sliding window matrix at this time:

$$\begin{aligned} R_{k+1} = R_k &- \frac{1}{L-1} x_{(k-L+1)}^T x_{(k-L+1)} \\ &- \Sigma_k^{-1} \Delta \hat{b}_k \Delta \hat{b}_k^T \Sigma_k^{-1} + \Sigma_{k+1}^{-1} \Delta \hat{b}_{k+1} \Delta \hat{b}_{k+1}^T \Sigma_{k+1}^{-1} \\ &+ \frac{1}{L-1} x_{(k+1)}^T x_{(k+1)} \end{aligned} \tag{22}$$

2.2.2 Sliding window PCA process

Based on the idea of data sliding window, this method replaces the earliest data in the sliding window with new data whose control quantity does not exceed the control limit, updates the principal component model in real time, and then detects the fault. The specific algorithm is as follows (Maozhenhua,2008):

(1) The principal component model is established according to the original data in order to determine the initial value of the sliding window principal component model.

(2) The sliding window moves forward to collect new data, and then standardize the new data.

(3) After the new data is standardized, the T^2 and Q statistics of the data are calculated. If the statistical value calculated from the data is less than or equal to the current control limit, turn to step (4), otherwise turn to step (2).

(4) Make this newly collected data replace the first data in the sliding form data. Calculate and update the initial value of the principal component model. Go to step (2).

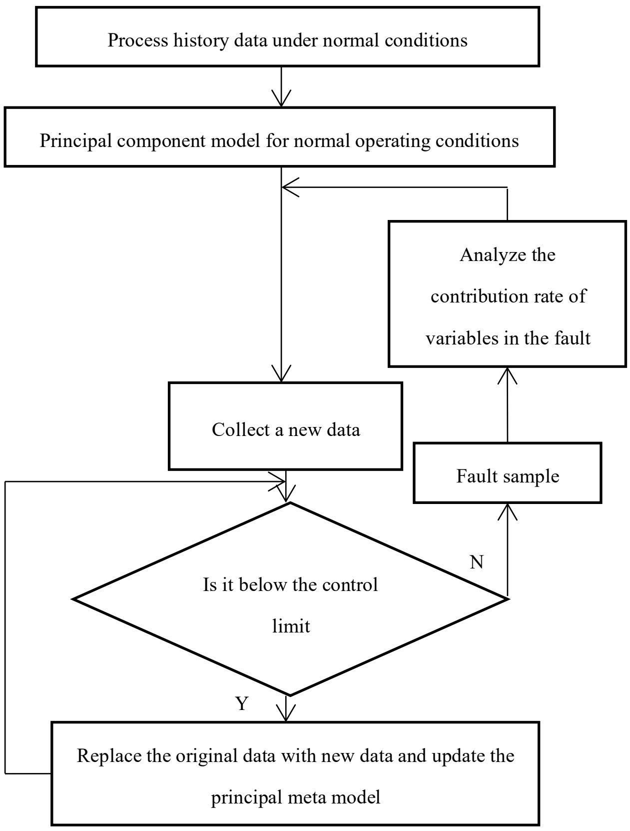


Fig.1. fault diagnosis flow chart of sliding window

3. Fault diagnosis based on Adaptive Principal Component Analysis

3.1 Characteristic gas data in transformer oil

A total of 125 sample data were collected in this paper, including 22 normal data samples, 43 discharge faults and 60 overheating faults. Each sample contains five characteristic gases of hydrogen, methane, ethane, ethylene and acetylene. The data are from literature (Xiong Hao, et al ,2005; Li jianpo,2008; L.V . Ganyun, et al,2004). Some sample books are shown in Tab.1.

Tab. 1. characteristic gas data in transformer oil

Sample serial number	hydrogen	methane	ethane	ethylene	acetylene
1	7.5	5.7	3.4	2.6	3.2
2	32	31	7.5	50	1.1
…	…	…	…	…	…
22	15.8	2.18	0.78	0.63	0
23	650	53	34	20	0
24	980	73	58	12	0
…	…	…	…	…	…
65	443	85	9.5	103	174
66	120	120	33	84	0.59
67	56	78	18	21	0
…	…	…	…	…	…
125	86	110	18	92	7.4

3.2 Characteristic gas in transformer oil and transformer fault

The specific characteristics of transformer overheating and oil discharge faults are different, such as tab.2.

Tab. 2. transformer fault types and characteristic gases

Classification of faults	Main gas in oil	Secondary gas in oil
Spark discharge in oil	H_2,C_2H_2	
Arc in oil	H_2,C_2H_2	CH_4,C_2H_4,C_2H_6
Arc in oil and paper	H_2,C_2H_2,CO,CO_2	CH_4,C_2H_4,C_2H_6
Oil overheating	CH_4,C_2H_4	H_2, C_2H_6
Oil and paper overheating	CH_4,C_2H_4, CO,CO_2	H_2, C_2H_6

3.3 T^2 and Q statistics of transformer samples

For the transformer fault diagnosis of principal component analysis, firstly, we should collect the data samples of the characteristic gas in the transformer oil during the normal operation of the transformer, establish a principal component model similar to the normal operation of the transformer, and then bring the collected data into the principal component model to calculate the degree of deviation of the data from the transformer model, so as to realize the fault diagnosis.

T^2 Statistics and Q statistics mainly reflect the degree of deviation of sample data from the principal component model. There are four possible test results for the statistical control chart:

(1) T^2 Statistics and Q statistics are greater than the control limit;

(2) T^2 Statistics is greater than the control limit, and Q statistics is less than the control limit;

(3) T^2 statistic is less than or equal to the control limit, and Q statistic exceeds the control limit;

(4) T^2 Statistics and Q statistics do not exceed the control limit;

It is generally considered that (1), (2) and (3) are abnormal states and (4) are normal states.

3.4 T^2 and Q statistics based on principal component analysis

The principal component model is established based on the data of 22 normal samples, and then the SPE and T statistics of all samples are calculated, as shown in Fig.2.

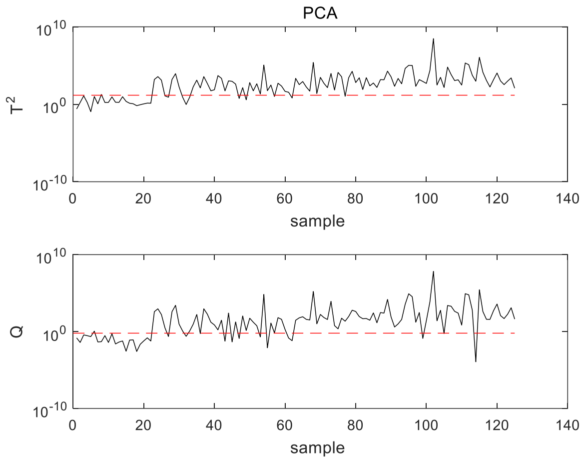


Fig.2. principal component analysis statistics

The results are shown in Figure 2. Most of the first 22 samples are lower than the control limit, and the samples after 22 are the samples after transformer fault. Most of the statistics are greater than the control limit, and there are false alarm points.

3.5 T^2 and Q statistics based on Adaptive Principal Component Analysis

The change of characteristic gas content in transformer oil has nonlinear and slow time-varying characteristics. In order to improve the accuracy of fault diagnosis, it is necessary to update the fault diagnosis model in real time. The sliding window PCA method is used to update the principal component model in real time, and the window length is set to 21. With the movement of the window, the normal data is used to replace the historical data to constantly update the principal component model. The simulation results are shown in Fig.3.

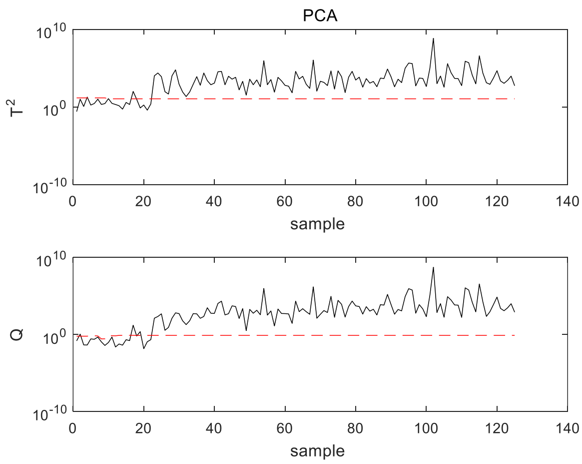


Fig.3. Adaptive principal component analysis

It is obvious from Figure 3 that the statistics of samples 23 to 125 are greater than the control limit. Compared with figure 2, sliding window PCA is more accurate.

3.6 transformer fault diagnosis based on contribution graph

When the T^2 statistic or Q statistic is greater than its control limit, it can be determined that the sample point deviates from the principal component model, that is, the sample point is abnormal. However, only according to the statistical control chart can not judge the cause and fault of the monitored components. The variables causing the component abnormality can be determined through the contribution diagram, so as to find out the cause of the abnormality. Contribution graph method is a common fault diagnosis method. The forms of contribution graph are diverse, and different algorithms can get different contribution graphs. Usually, when the abnormal sample in the sample is obtained according to T^2 statistic and Q statistic control chart, it is considered that the industrial time represented by that sample has failed, and then the contribution diagram in the form of histogram is drawn. Using the contribution graph, we can not only directly see the contribution rate of each variable, but also find the key variables. It is generally considered that the key variable is the variable with the largest contribution rate. After finding the key variables, analyze them in combination with professional background knowledge, so as to preliminarily recognize the cause of the fault and find the fault.

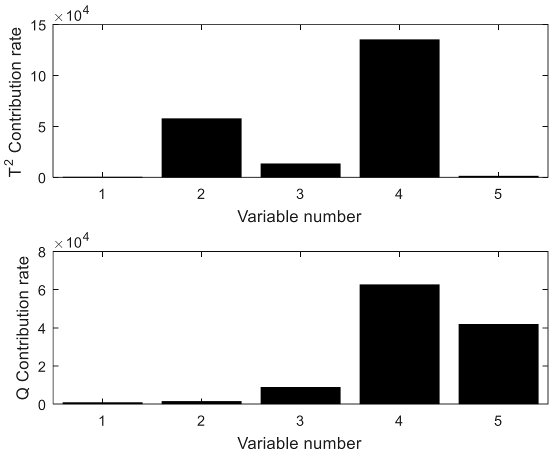


Fig.4. Contribution diagram of variables of sample 121

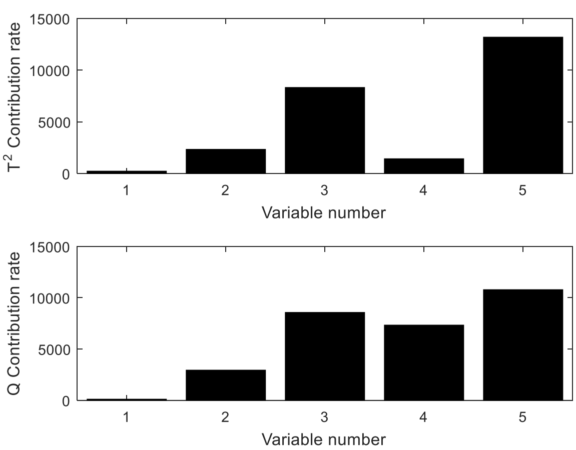


Fig.5. Contribution diagram of variables of sample 45

According to the sample points with abnormal work determined by the statistical control chart, the contribution diagram of each variable of the abnormal sample can be drawn. The key can be found by analyzing the image according to tab.2. so as to determine the cause of the abnormality. As shown in Fig.4. variable 1, variable 2, variable 3, variable 4 and variable 5 represent H_2, CH_4, C_2H_6, C_2H_4 and C_2H_2 in turn. According to the contribution diagram, it can be seen that the contribution rate of variables 2 and 4 is the largest, that is, CH_4 and C_2H_4 are the main causes of faults. Determine the transformer overheating fault according to tab.2.

As shown in Fig.5. it can be found that C_2H_6 and C_2H_2 are characteristic gases with relatively large contribution. According to tab.2. This is a discharge fault of the transformer.

4. Conclusion

Through the characteristic gas data of transformer during fault and normal conditions collected from the literature, aiming at the problem of transformer fault detection and diagnosis, a principal component model covering the characteristic gas data in transformer oil during normal operation of transformer is established by using the method of principal component analysis, and the operation state of transformer components is monitored through statistical control chart, It is found that the principal component analysis method has good effect in transformer operation monitoring. In order to adapt to the slowly changing working conditions, the idea of sliding window is added on the basis of principal component analysis to realize the adaptive update of transformer principal component model, and the distinction between transformer discharge fault and overheating fault is realized by using contribution graph.

References

[1] Fang Ning. Research on modeling analysis and monitoring of wind turbine components based on principal component analysis method. 2014. North China Electric Power University, MA,thesis.

[2] Tang Yongbo, Ou yangwei. "Application of principal component analysis in transformer fault detection and identification." computer application and software 27.04 (2010): 224-226+260.

[3] Tang Yongbo, GUI Weihua, and Ou Yangwei. "Application of principal component analysis and reconstruction contribution in transformer fault detection and diagnosis." mechanical science and technology 31.02 (2012): 206-212.

[4] Xuan Jiyang. Research on micro fault diagnosis based on principal component analysis and contribution graph. 2015. Zhejiang University, MA thesis.

[5] Wen daosong. Industrial process fault detection and diagnosis based on improved principal component analysis. 2011. Harbin University of technology, MA thesis.

[6] Wei Jie. Research on motor condition monitoring method based on principal component analysis. 2009. Beijing Jiaotong University, MA thesis.

[7] Zhu Kongwei. Fault detection and diagnosis of power plant boilers based on principal component analysis. 2006. Southeast University, MA thesis.

[8] Maozhenhua. Research on adaptive process monitoring method based on principal component analysis. 2008. Zhejiang University, MA thesis.

[9] Huang Xiaobin, Liu Jizhen, Niu Yuguang. "Application of principal component analysis method in boiler process fault detection in thermal power plants." power engineering.04 (2004): 542-547.

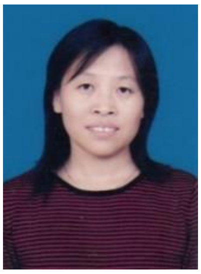
[10] Huang Xiaobin, Niu Zheng, Niu Yuguang, Liu Jizhen. "Behavior analysis of sensor fault detection using principal component method." Journal of sensing technology.04 (2003): 419-423.

[11] Xiong Hao, sun Caixin, Liao Ruijin, Li Jian, Du Lin. "Research on fault diagnosis of power transformer based on nuclear possibility clustering algorithm and analysis of dissolved gas in oil." Proceedings of the CSEE.20 (2005): 162-166.

[12] Li jianpo. Research on Fault Diagnosis Technology of power transformer based on analysis of dissolved gas in oil. 2008. Jilin University, phD dissertation.

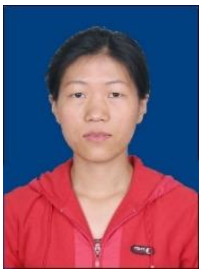
[13] L.V. Ganyun, et al."Fault diagnosis of power transformer based on multi-layer SVM classifier." Electric Power Systems Research 74.1(2004).

[14] Zhao Lijie, Chai Tianyou, Wang Gang. "Research progress of multivariate statistical performance monitoring and fault diagnosis technology." information and control. 02 (2004): 197-201.

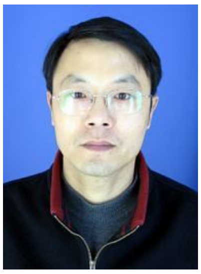


Du Wenxia obtained her master degree and doctor degree of control theory and control engineering major from the institute of electrical engineering of Yan Shan University in 2001 and 2012 respectively. She is currently working in Hebei Normal University. Her main research interests are in area of neural network control and predictive control of nonlinear system, the fault diagnosis based on data driven is her new research direction in recent years.

Ning Yang is currently studying for a master's degree at the College of Electrical Engineering, Northeast Electric Power University, Jilin, China. In 2021, he received a Bachelor of engineering degree from Hebei Normal University, China.



Du Hailian obtained her master degree control science and control engineering major from the Department of Automation of North China Electric Power University in 2006. She is currently working in Hebei Normal University. Her main research interests are in area of neural network control and information fusion, the fault diagnosis based on data driven is her new research direction in recent years.



Xin Tao, associate professor, graduated from yanshan University in 2004, with a master's degree in instruments science and technology. He is working in the vocational and Technical College of Hebei Normal University, his main research interests are automatic control technology and fault diagnosis.

Wang Yanhong graduated from southwest jiaotong university in 2010, with a master's degree in power system and automation. At present, she is working in the vocational and Technical College of Hebei Normal University, as a teaching job, and her research direction: research direction of power system relay protection.