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Fault diagnosis of electrical system based on SVM optimization of neural network with directed factor diagram

Zhongwang Li[1], Yu Ni[2]

Abstract. In order to solve rapid failure recognition problem in value-added service mode of specific transformer user, the online recognition method on power equipment failure of specific transformer user is designed based on measurement automation and integration platform. The method establishes auto-regressive model on time series of state parameter of specific transformer equipment based on measurement automation and integration platform, and uses self-organized maps to quantify time series as system input value. By using process input in sliding time window to establish learning sample of least square support vector machines, the deviation between its regression calculation result and measured value of feature vector of model is set as observed value. The Gaussian mixture model is used to fit multi-dimensional observed value distribution to construct system background model. The failure index is calculated through matching degree of new individual observed value and background model to realize real-time recognition of equipment failure. Experimental result shows that the method can realize rapid and correct online failure prediction.

Key words. Self-organized maps, Electrical equipment, Failure diagnosis, Failure index, Online failure recognition.

1. Introduction

As key and major state-owned enterprise, the power company integrates public welfare, service and monopoly. Under the guidance of strategic objective of "one strong and three excellent" construction, massive amounts of business data have been accumulated because of wide application of its information technology, and specific transformer user needs high-quality service of higher quality because of delicacy management demand and company management efficiency improvement purpose, so rapid detection and positioning of failure becomes one of the main at-

[1]Department of Electrical Engineering, Wuhu Institute of Technology, Wuhu, China
[2]Shanghai Orient Software Technology Co, Ltd., Shanghai, China

tention directions [1]. Because of natural environment impact, device aging and overload etc. [2, 3] in operation process of power equipment, equipment performance has been degraded gradually and equipment even has failure. At present, threshold determination methods are mainly used for failure recognition and positioning [4], but such methods generally have limitations and hysteresis. Because power equipment is characterized by numerous data types and large data etc., large data technology is introduced for equipment state detection, and abnormal state of equipment is analyzed and detected through big data [5]. However, there are also some difficulties[6-8] in abnormal detection of power equipment. The first difficulty is how to quickly detect abnormal data of small scale transformer in massive normal data, and the second one is that relationship among each state parameter cannot be described through specific function easily. There are some defects in the existing detection space partitioning algorithm and time series model algorithm, etc. [9] Based on measurement automation system of power system, and combining with auto-regressive (AR) model and self-organized maps (SOM), this paper establishes data flow quantification input, and calculates equipment failure prediction index in real time through least square support vector machines (LSSVM) and Gaussian mixture model (GMM).

2. Overall design of system

At present, Dongguan Shipai State Grid has established measurement automation and integration platform of power enterprises, of which structure is as shown in Figure 1. Power equipment of public transformer user and specific transformer user at terminal layer is accessed to front acquisition layer of platform through power communication network and public communication network of remote communication, and enters into business processing layer through data exchange processing layer for 4 kinds of function management, i.e. meter-reading at low voltage, measurement of public transformer, value-added services of specific transformer and load management. Back-end integrated application layer includes demand side management and quarter line losses. Through measurement integration platform, State Grid can make data processing and provide value-added services according to all information acquired on specific transformer equipment. Online failure recognition system in this paper is established based on measurement automation platform, so as to provide value-added services for specific transformer user through big data analysis.

Main flow of system is as shown in Figure 2. AR simulation fitting is firstly made to state parameter, data flow quantification input is established through SOM, and observed value of system is calculated through SSVM to train background model of system and calculate equipment failure index in real time to achieve real-time failure recognition.

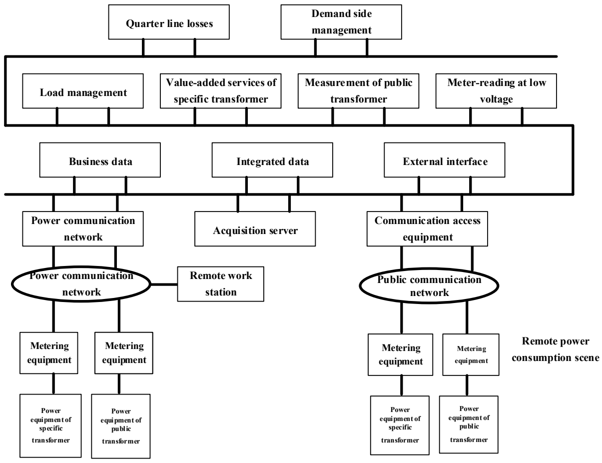

Fig. 1. Structure of measurement automation and integration platform

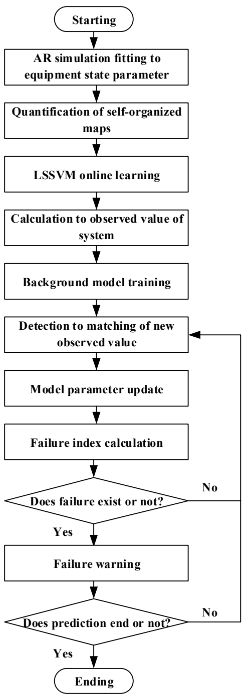

Fig. 2. Online failure recognition flow

3. Modeling and quantification of specific transformer equipment

3.1. Auto-regressive model of time series

Auto-regressive model of time series is applicable to a large number of industrial processes [10], of which advantage is strong memory, and the value of a certain time is related to previous time behavior. Grounding current, conductor tension and other parameters of power equipment of specific transformer user has relatively small change, which can be classified into stationary series. Although environment temperature, oil temperature and other parameters present periodical change, their change amplitude is relatively small, and also belong to stationary series after periodicity removal, and can be fitted with $AR(1)$. Assumed that online monitoring data at moment t is $x(t)$, and state parameter model through AR simulation fitting is as shown in formula (1).

$$x(t) = \alpha \cdot x(t-1) + e(t) = \alpha^t \cdot x(0) + \sum_{i=0}^{t-1} \alpha^i \cdot e(t-i) . \tag{1}$$

Where, $\alpha < 1$, $e(t) \sim N\left(\mu_e, \lambda^2\right)$ is normal distribution sequence, and $x(t) \sim N\left(\mu, \sigma^2\right)$ can be obtained and:

$$\mu = \mu_e / (1-\alpha) . \tag{2}$$

$$\sigma^2 = \left(\alpha^2 \mu^2 + \lambda^2 + \mu_e^2\right) / \left(1-\alpha^2\right) . \tag{3}$$

State monitoring requires that the number of states shall not exceed the specified threshold, which means that $x(t)$ of each corresponding moment t shall meet $x(t) \in [a, b]$, and followings can be obtained:

$$\begin{aligned} & a - \alpha^k x(t) \leq e(t+k) + \alpha e(t+k-1) + \cdots + \\ & \alpha^{k-1} e(t+1) \leq b - \alpha^k x(t) \end{aligned} \tag{4}$$

According to formula (4), assumed that when specific threshold α_0 exists, $x(t) \in [a, b]$ will only be workable when $\alpha < \alpha_0$. As power equipment has slow latent failure changes, monitoring data does not exceed set threshold under equipment abnormity, which is the defect caused when state monitoring is made merely through AR model, thus, model shall be optimized further.

3.2. Quantification of time series

Since state data of equipment is free from label and has large data size, self-organized maps can be used to make unsupervised learning, to quantify time series [11]. SOM takes the whole sequence $x(t)$ as input, with $O = [O_1, O_2, \cdots, O_N]$ as output, and corresponding training formula on $x(t)$ and output node O_j is:

$$j = i(x(t)) = \arg\min_i d(x(t), O_i(t)) \ . \tag{5}$$

Minimize distance between $x(t)$ and corresponding output node through modification and repeated iterations, which is as shown in formula (6).

$$\begin{cases} O_i(t+1) = O_i(t) + \beta(t)(x(t) - O_i(t)) & i \in N_i(t) \\ O_i(t+1) = O_i(t) & i \notin N_i(t) \end{cases} \tag{6}$$

Where, $\beta(t) \in (0,1)$ is learning rate. Transform the whole sequence $x(t)$ into time series $O(t) \in \{O_1, O_2, \cdots, O_N\}$ of discrete point in linear space through SOM quantification, and $O(t)$ can be expressed as:

$$O(t) = O_i(x(t)) \tag{7}$$

4. Online failure recognition design

A multiple input system is generated through AR modeling on state monitoring parameter of power equipment of specific transformer and SOM treatment quantification, but online failure recognition and relationship among numerous state parameters are extremely complex, which can not be accurately described through function. In addition, data flow is relatively great in operation process of equipment, so big data analysis method is used, and LSSVM is used for rapid state classification to realize failure recognition.

4.1. LSSVM online learning

LSSVM maps input data to high-dimensional feature space [12] through nonlinear mapping, transforms nonlinear function problem of low-dimensional space into linear function estimation problem of high-dimensional space, and transforms regression problem into constrained quadratic programming problem.

$$\begin{cases} \min\left(\frac{1}{2}\|\omega\|^2 + \frac{C}{2}\sum_{i=1}^{n}\xi_i^2\right) \\ s.t.\ \omega^{\mathrm{T}}\varphi_i(x_i) + b + \xi_i = y_i \end{cases} \tag{8}$$

Where, ξ_i is slack variable, and C is penalty factor, Lagrange function can be obtained by introducing Lagrange multiplier and kernel function $k(x_i, x_j)$ is introduced to obtain regression function finally:

$$y(x) = \sum_{i=1}^{n} \lambda_i k(x_i, x) + b\,. \tag{9}$$

When it is used for online modeling of time-varying process, process amount of sliding time window shall be used to establish learning sample. As dynamic performance requires that time window F shall not be overlong, the incremental learning algorithm shall be adopted. Sample set $\{(x_i, y_i)\}_{i=1}^{i=l}$ has been expanded gradually with time, regression function parameter a and b of LSSVM and kernel matrix Q change with it, and linear equation set is updated as follows:

$$\begin{bmatrix} 0 & e1^T \\ e1 & Q(l) + C^{-1}I \end{bmatrix} \cdot \begin{bmatrix} b(l) \\ a(l) \end{bmatrix} = \begin{bmatrix} 0 \\ y(l) \end{bmatrix}. \tag{10}$$

Where, $e1 = [1, 1, \cdots, 1]^T$ and its solution is:

$$b(l) = \frac{e1^T \left(Q(l) + C^{-1}I\right)^{-1} y(l)}{e1^T \left(Q(l) + C^{-1}I\right)^{-1} e1}. \tag{11}$$

$$a(l) = \left(Q(l) + C^{-1}I\right)^{-1} \left(y(l) - e1 \cdot b(l)\right). \tag{12}$$

Regression function can be obtained as:

$$y(x, l) = \sum_{i=1}^{l} a(l) \cdot k(x_i, x) + b(l) \tag{13}$$

The process of obtaining regression function mainly changes into $Q(l) + C^{-1}I$ calculation, and followings can be obtained when new sample $\{(x_{l+1}, y_{l+1})\}$ is added:

$$Q(l) + C^{-1}I = \begin{bmatrix} Q(l) + C^{-1}I & M(l+1) \\ M(l+1) & m(l+1) \end{bmatrix}. \tag{14}$$

Where, $M(l+1) = [k(x_{l+1}, x_l), \cdots, k(x_{l+1}, x_l)]^T$, $m(l+1) = k(x_{l+1}, x_{l+1}) + 1/C$, and based on which recurrence calculation of $H(l)^{-1}$ can be finished through inversion formula of partitioned matrix, and online learning algorithm can be finished.

4.2. State recognition algorithm

Study has verified that in the case of abnormity of system state, LSSVM regression calculation result and feature vector would have relatively great deviation, i.e. observed value, and its calculation formula is as shown in formula (15).

$$\sigma_j = \left[\sqrt{(a_1 - a_1')}, \cdots, \sqrt{(a_m - a_m')}\right]. \tag{15}$$

Where, m is vector dimension of observed value of system, a_i is measured value of the ith variable of feature vector y, and a' is output feature value of corresponding LSSVM model. In initial stage of failure, most measured values are normal data, with relatively small abnormal value proportion and theoretical threshold is rarely exceeded, and therefore, the idea of background elimination detection in current image processing is introduced [13] where it is set as a failure background after normal state is recognized to recognize subtle change in initial stage of failure. Assumed that occurrence probability of observed value x_i at the ith moment is weighted sum of probability with corresponding value belonging to individual Gaussian distribution, i.e.:

$$p\left(x|\Theta\right) = \sum_{k=1}^{K} w_{k,i} N_k \left(x|\mu_k, C_k\right). \tag{16}$$

Where, $x = [x_1, x_2, \cdots, x_m]$ is m-dimensional observed column vector, $\Theta = [w_k, \mu_k, C_k]$ is all parameter sets, and $N_k\left(x|\mu_k, C_k\right)$ is the kth Gaussian distribution, with mean value being μ_k, variance being C_k, and $w_{k,i}$ is prior probability of $x_k \in N_k\left(x|\mu_k, C_k\right)$. Assumed that sample $X = \{x_1, x_2, \cdots, x_N\}$ has likelihood function $L\left(\Theta|X\right)$, then:

$$\log\left(L\left(\Theta|X\right)\right) = \sum_{j=1}^{N} \log p\left(x_j|\Theta\right). \tag{17}$$

In initial operation process, initial value of C_k of each $N_k\left(x|\mu_k, C_k\right)$ is unit matrix, $w_{k,i} = 1/K$, and μ_k is the first observed value, so prior probability of new observed value $x_k \in N_k\left(x|\mu_k, C_k\right)$ can be obtained as:

$$p\left(k|x_j, \Theta^h\right) = \frac{w_k N_k\left(x_j, \Phi^h\right)}{\sum\limits_{k=1}^{K} w_k N_k\left(x_j, \Phi^h\right)}. \tag{18}$$

Where, Φ^h is old parameter, and mean value $\mu_{k,t-1}$, covariance matrix $C_{k,t-1}$ and prior probability $w_{k,t-1}$ shall be respectively updated according to observed value newly calculated, and make repeated iteration until formula (19) is met:

$$\left|\log\left(L\left(X|\Phi^h\right)\right) - l\hat{o}g\left(L\left(X|\Phi\right)\right)\right| < \varepsilon. \tag{19}$$

Where, $\log\left(L\left(X|\Phi^h\right)\right)$ is calculated through formula (17), ε does not exceed 10^{-5} generally, and $l\hat{o}g\left(L\left(X|\Phi\right)\right)$ is calculated value after parameter update.

In order to provide system background, k distribution is ranked according to size of $w_k \big/ \|\sigma_k\|^2$, where σ_k is standard deviation of the kth distribution, and w_k is element weight of the kth distribution. Set the first C distribution with total cumulative probability exceeding T as background system, and C shall meet conditions of formula (20):

$$C = \arg\min_{C}\left(\sum_{k=1}^{C} w_k > T\right). \tag{20}$$

Where, T is the probability that any observed value of system belongs to background system, and is overall prior probability actually. Judging failure after system background confirmation means to find new emerging individual in background system. Firstly, whether observed value x_t of new individual is matched with background, i.e. existing K Gaussian distribution shall be judged firstly:

$$\begin{cases} d_{k,t}^{T} d_{k,t} < \lambda^2 \\ d_{k,t} = (\sigma_{k,t} I)^{-1} (x_t - u_{k,t}) \end{cases} \tag{21}$$

Where, λ is constant with value range being $[2, 3]$.

If x_t is matched with background, the mean value, covariance matrix and prior probability shall be respectively updated according to observed value newly calculated, variance and expected value shall be kept unchanged and other Gaussian model weight decreases. After that, failure index I_{FP} is updated as:

$$I_{FP} = \frac{1}{\alpha} \sum_{t=1}^{\alpha} \left(-\ln \left(\sum_{k=1}^{n} w_k N_k \left(x_t | k; \mu_k, C_k \right) \right) \right). \tag{22}$$

Where, α is sliding window, being used to reduce misjudgment rate, and the greater its value is, the higher the historical value weight will be. After that, new observed value shall be judged repeatedly.

5. Experimental verification

Manually set potential failure for 220Kv transformer of Dongguan Shipai specific transformer equipment to make system performance detection, and to reduce power limit factor effect, power equipment is relatively close (roughly 3.4km) to power center, and data is transmitted through power communication network. Main parameter setting of system is as shown in Table 1.

Table 1. Main parameter setting

No.	Parameter name	Parameter value
1	C	30
2	β^2	9
3	F	5
4	α	0.8
5	μ_ε	0
6	λ	0.01
7	K	15
8	T	0.7
9	ε	$7 \bullet 10^{-6}$
10	Sampling period	1s

Taking transformer load, oil temperature and environment temperature and other real-time data as monitoring object, the prediction error between observed value and true value obtained is as shown in Fig.3 taking an example of load, It can be found from the figure that the prediction accuracy of LSSVM model reaches to relatively high level after 55 sampling periods.

In order to detect system failure prediction sensitivity, transformer load is manually set to be abnormal. To improve security, failure setting exists in model input end, the load rate is raised by program to make load rate be[75% , 85%], in such case, long-time work will cause transformer failure and failure index obtained is as shown in Fig. 4. Keeping time from load increase setting starting, failure index is gradually increased, and failure index begins to increase significantly after about 14 seconds, although there are some fluctuations, overall trend is on the rise, and after maintaining abnormal state of load for about 90 minutes, the transformer is alarmed for failure, but system can reflect the equipment abnormity in real time according to failure index within 14 seconds, which verifies that the system has relatively high sensitivity on failure prediction.

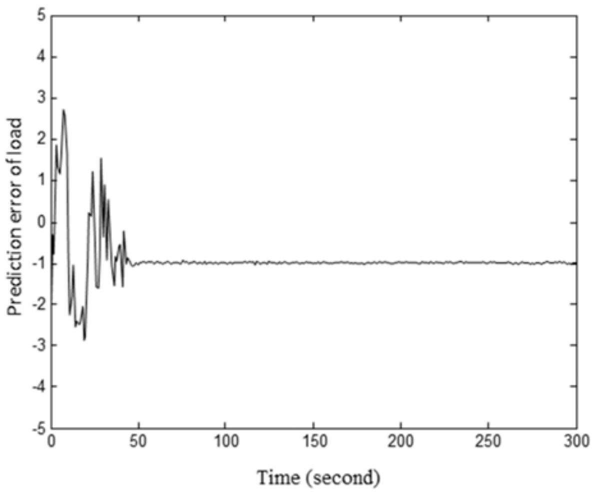

Fig. 3. Prediction error of load

6. Conclusion

The automatic failure detection method for power equipment of specific transformer user is designed in this paper designs by combining with existing measurement automation and integration platform. The observed value is generated with regression calculation result of last square support vector machines and measured value by monitoring real-time data, such as power equipment load, oil temperature, environment temperature and other real-time data. The failure index is calculated by matching degree of new observed value and background model to realize online failure recognition, so as to predict healthy state promptly before equipment failure, and its sensitivity and promptness have been verified. Emphasis of next step is to expand system monitoring state parameter monitoring algorithm to improve system model.

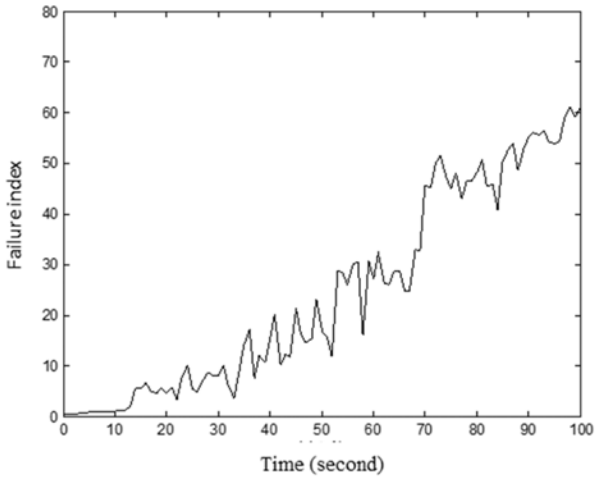

Fig. 4. Failure index calculation result

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