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A GD-SVM Model for Calculating Oil-Immersed Transformer Hot Spot Temperature

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A GD-SVM Model for Calculating Oil-Immersed Transformer Hot Spot Temperature

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Abstract. With the rapid development of power grid, the equipment of power grid is more and more intensive, and the requirement of reliability is higher and higher. Oil-immersed transformer is one of the most critical equipment in power system. Its operation reliability is directly related to the safety and stability of the whole power grid. When transformer fault occurs, even under the same external operating environment, the hot spot temperature is different from the normal hot spot temperature. Generally, when the transformer overheat fault occurs, the hot spot temperature is usually higher than the normal hot spot temperature, and different fault modes will also cause different temperature variations of the transformer hot spot. By analyzing the variation law of the transformer hot spot temperature under different faults, it is helpful to evaluate and predict the load capacity of the transformer in real time and ensure the safety operation of the transformer. Hot spot temperature is a factor of measuring transformer performance, and it is also the most important limiting factor of transformer load capacity. It is also related to transformer safety and reliability, service life and manufacturing cost. Therefore, accurate calculation and prediction of the hot spot temperature has great significance for reasonable using transformer. Therefore, a support vector machine thermal calculation model based on gradient descent method is proposed in this paper. The validity and feasibility of the model are verified by the comparison of calculation and experiment results.

1. Introduction

With the rapid development of China's industry, commerce and the improvement of residents' living standards, the electricity consumption of residents, industry and commerce presents a growing trend and the social stability and development require adequate and stable power supply. In such an environment, the scale of China's power grid keeps expanding, the construction speed keeps increasing, and major breakthroughs have been made in the power transmission and transformation technologies of ultra-high voltage and ultra-high voltage [1-3].

When the transformer breaks down, it may cause serious impact on the power system [4]. If it is ignored, it will cause a large area of power failure and even severe social impact of substation fire. When the transformer breaks down, even in the same external operating environment (climate, load, geographical location), the hot spot temperature is different from the normal hot spot temperature. Generally, when the transformer overheat fault occurs, the hot spot temperature is usually higher than the normal hot spot temperature, and different fault modes will also cause the change of the hot spot temperature of the transformer to different degrees.

At present, for transformer hot spot temperature calculation, there are: guide recommended calculation method, numerical calculation method, thermal path model calculation method and intelligent algorithm calculation method, and the transformer winding hot spot temperature calculation model recommended by standard guide is widely adopted in engineering [5-6], but it has limitations and no intuitive physical meaning. In this paper, a heat prediction model of support vector machine based on gradient descent optimization is proposed, which can solve the above problems and provide an effective way for the calculation of hot problems of transformer [7-8].

At the same time, this paper takes transformer for research, which processes the sample set of oil-immersed transformer, and uses GD-SVM model to realize the hot spot temperature prediction of oil-immersed transformer. It can provide data basis for the load capacity evaluation of transformer.

2. GD-SVM heat prediction model

2.1. Sample pretreatment

Different types of data have different data dimensions and measurement range. In order to ensure the accuracy of the prediction results, it is necessary to normalize all types of data and change all types of data to the same range. The commonly used normalization methods are the maximum minimum method, maximum method and mean standard deviation method. In this paper, the maximum minimum method is adopted to normalize the heat temperature prediction data to the range $[0,1]$. Set the sequence $x_0 = \{x_0(1), x_0(2), \cdots x_0(N)\}$, the normalized data $x_1 = \{x_1(1), x_1(2), \cdots x_1(N)\}$, and the normalization formula is as shown in the formula:

$$x_1 = \{x_1(1), x_1(2), \cdots x_1(N)\} \tag{1}$$

2.2. Gradient descent algorithm

For the training set $\{x^{(i)}, y^{(i)}\}$, $h_\theta(x)$ is assumed to be the fitted function, $J_\theta(x)$ is the loss function Cost function, θ is the parameter, m is the number of samples of the training set, and n is the number of features [9].

$$h_\theta(x) = \sum_{j=0}^{n} \theta_j x_j \tag{2}$$

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(y^{(i)} - h_\theta(x^{(i)}) \right)^2 \tag{3}$$

Repeat until convergence {

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \text{ simultaneously update } j = 0 \text{ and } j = 1 \tag{4}$$

}

α is the step length. Finally, the optimal solution can be obtained:

$$\theta_j' = \theta_j - \frac{\partial J(\theta)}{\partial \theta_j} = \theta_j + \frac{1}{m} \sum_{i=1}^{m} \left(y^{(i)} - h_\theta(x^{(i)}) \right) x_j^i \tag{5}$$

2.3. Support vector machine algorithm

I is assumed to be the load current of transformer, ambient temperature is θ_e, top oil temperature is θ_{top}, bottom oil temperature is θ_{btm}, top dead angle oil temperature of oil tank θ_1, bottom dead Angle oil

temperature of oil tank is θ_2. The above characteristic quantity is the input quantity of SVM, and the winding hot temperature θ_h is the output quantity.

Training sample set is $\{(x_i, y_i), i = 1, 2, \cdots, n\}$, $x_i \in R^n$.

$y_i \in R$. $x_i = \left[I, \theta_e, \theta_{top}, \theta_{btm}, \theta_1, \theta_2 \right]$ is the input column vector for the i sample. The output value is $y_i = [\theta_h]_i$.

The sample is mapped to a higher dimensional space by $\varphi(x)$, and the linear regression function is established by minimization of structural risk:

$$y' = \theta_h(x) = w \cdot \varphi(x) + b \tag{6}$$

Where y' is the predicted value corresponding to the regression function, w is the weight vector, $w \in H$ and $b \in R$ is the bias.

Define ε is linear insensitivity loss function

$$L(\theta_h(x), y, \varepsilon) = \begin{cases} 0, & |y - \theta_h(x)| \le \varepsilon \\ |y - \theta_h(x)| - \varepsilon, & |y - \theta_h(x)| \le \varepsilon \end{cases} \tag{7}$$

Considering the fitting error, the relaxation factor ξ_i, ξ_i^* is introduced, and the regression problem is transformed into the solution of the objective function minimization of w and b.

$$\begin{cases} \min \left\{ \dfrac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \left(\xi_i + \xi_i^* \right) \right\} \\ s.t. \begin{cases} y_i - w \cdot \varphi(x_i) - b \le \varepsilon + \xi_i \\ w \cdot \varphi(x_i) - y_i + b \le \varepsilon + \xi_i^* \\ \xi_i \ge 0, \xi_i^* \ge 0 \end{cases} \end{cases} \tag{8}$$

Lagrange function is constructed by introducing non-negative Lagrange multiplier. Partial derivatives of all variables are obtained and set to zero. By virtue of the duality principle, it is transformed into solving the duality problem:

$$\begin{cases} \max_{\alpha, \alpha^*} \left\{ -\dfrac{1}{2} \sum_{i,j=1}^{n} \left(\alpha_i - \alpha_i^* \right)\left(\alpha_j - \alpha_j^* \right) K(x_i, x_j) - \varepsilon \sum_{i=1}^{n} \left(\alpha_i + \alpha_i^* \right) + \sum_{i=1}^{n} y_i \left(\alpha_i - \alpha_i^* \right) \right\} \\ s.t. \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^* \right) = 0 \quad \alpha_i, \alpha_i^* \in [0, C] \end{cases} \tag{9}$$

We get the optimal solution $\alpha = [\alpha_1, \alpha_2, \cdots, \alpha_n]$, $\alpha^* = [\alpha_1^*, \alpha_2^* \cdots \alpha_n^*]$. So we get w and b as followed:

$$w = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^* \right) \varphi(x_i) \tag{10}$$

$$b = \frac{1}{N} \left\{ \sum_{0 < \alpha_i < C} \left[y_i - \sum_{x_i \in SV} \left(\alpha_i - \alpha_i^* \right) K \left(x_i, x_j \right) - \varepsilon \right] + \sum_{0 < \alpha_i < C} \left[y_i - \sum_{x_j \in SV} \left(\alpha_j - \alpha_j^* \right) K \left(x_i, x_j \right) + \varepsilon \right] \right\}$$
(11)

N is the number of support vector machines.

$$\theta_h \left(x \right) = w \cdot \varphi \left(x \right) + b = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^* \right) K \left(x_i, x_j \right) + b$$
(12)

Where α_i, α_i^* is the non-negative Lagrange multiplier and $K \left(x_i, x_j \right)$ is the kernel function satisfying the Mercer condition. In this paper, RBF kernel function is adopted [10]:

$$K \left(x_i, x_j \right) = \exp \left(-\gamma \left\| x_i - x_j \right\|^2 \right)$$
(13)

The kernel is $\gamma > 0$. The European norm is $\left\| x_i - x_j \right\|$.

2.4. Model predictive steps
In this paper, a GD-SVM oil-immersed transformer hot-spot temperature prediction model is proposed. The prediction steps are as follows:
    Step 1. Normalization processing of data samples;
    Step 2.Determine the optimal interval and value of the parameters;
    Step 3.Establish SVM regression prediction model and use GD algorithm to optimize SVM parameters;
    Step 4.Obtain the optimal SVM parameter combination;
    Step 5.Obtain the predicted value.
    The GD algorithm was used to optimize the penalty factor C and kernel parameter γ, and the optimization interval was set as $[0, 40]$ and $[0, 400]$ respectively. The step length α was 0.01. $\gamma = 0.34$ and $C = 1.21$ were finally obtained

3. Experiment
In this paper, oil-immersed transformer is selected as the experimental object to collect the sample data, Under the condition of the same current, the transformer is operated continuously for 24 hours, and a total of 360 sets of data are collected during the experimental time. Among them, 340 groups are used as training set samples and 20 groups as prediction set samples.
    In order to verify the performance of GD-SVM hot spot temperature prediction method proposed in this paper, BP neural network is adopted for comparison. The following predicted output values are obtained. The curves of predicted and actual values of GD-SVM and BP neural network are shown in figure 1.
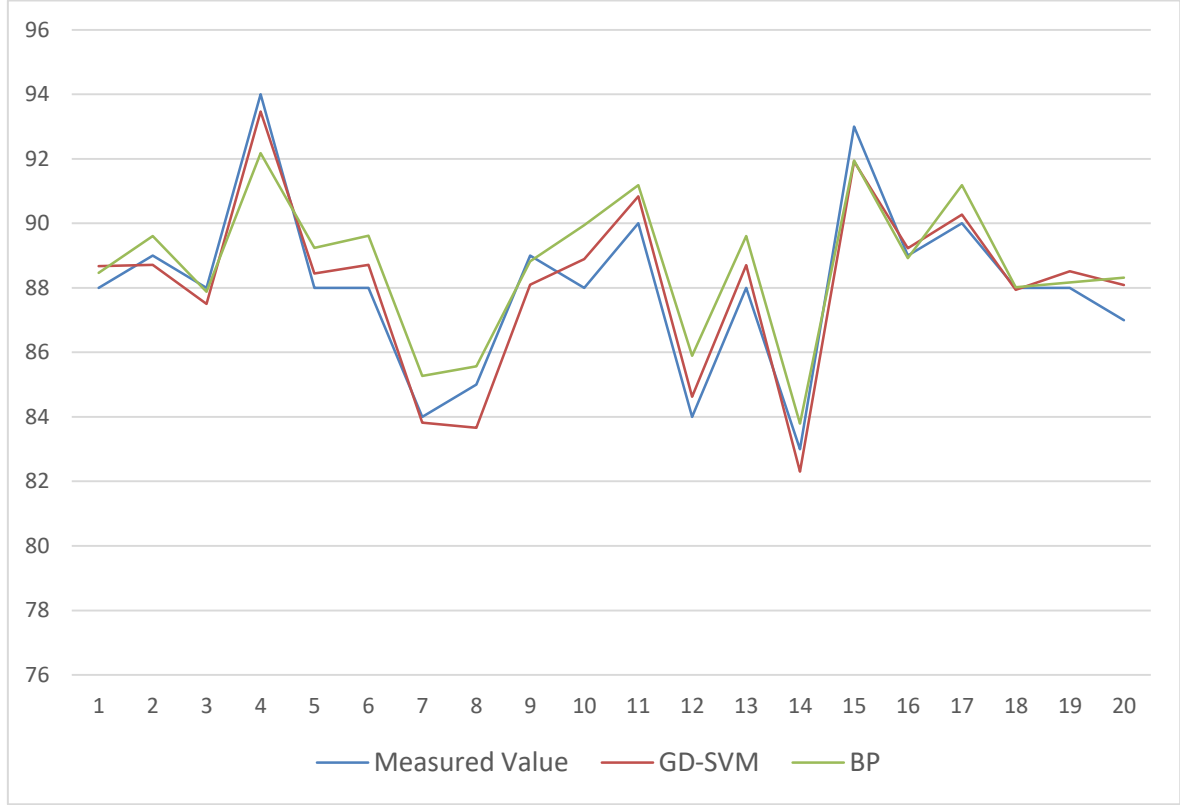
Figure 1. Curves of measure value GD-SVM and BP

To verify the accuracy of GD-SVM oil-immersed transformer hot-spot temperature prediction method, two indicators are introduced in this paper. Mean squared error (MSE) and correlation coefficient (R) were used to evaluate the performance and prediction results of the model. The smaller the MSE value is and R get closer to 1 , the better the predicted performance is [11-12].

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(y_i^{'} - y_i\right)^2 \tag{14}$$

$$R = \sqrt{\frac{\left(m\sum_{i=1}^{m} y_i^{'} y_i - \sum_{i=1}^{m} y_i^{'} \sum_{i=1}^{m} y_i\right)}{\left(m\sum_{i=1}^{m} y_i^{'2} - \left(\sum_{i=1}^{m} y_i^{'}\right)^2\right)\left(m\sum_{i=1}^{m} y_i^{2} - \left(\sum_{i=1}^{m} y_i\right)^2\right)}} \tag{15}$$

The actual value and the calculated predicted value of GD-SVM and BP neural network are respectively calculated by the above formulas.

Table 1. Comparison of model performance

Modeling method	MSE	R
GD-SVM	0.5073	0.959
BPNN	1.313	0.916

The experiments results are shown in table 1. The results show that the MSE of GD algorithm is the smallest and R is the closest to 1, so the prediction accuracy is optimal.

4. Conclusions

In this paper, the proposed GD-SVM transformer hot spot temperature prediction model, using the advantage of generalization ability of support vector machine (SVM), by the use of RBF function to train and forecast samples, the prediction accuracy is relatively high, and this can be used for the temperature monitoring of transformer hot spots. Through the analysis of the changing rule of transformer hot temperature, which can give much convenience to the real-time assessment and prediction of load capacity of transformer. Consequently, the stability operation of transformer can be guaranteed. The application results of this paper that have been deployed in Shandong power grid. This module effectively makes up for the calculation accuracy of the hot spot temperature in the existing platform, and it can realize the statistical analysis of hot spot temperature of the equipment, providing useful benefits for the better operation and maintenance of the equipment.

References

[1]   G.W.,Zocholl,S.E.,Bajpai,M.,Burger,J.F.,Castro,C.H.,Chano,S.R.,Cobelo,F.,De   S á P.,Fennell, E.C.,Gilbert,J.G.,Grier,S.E.,Haas,   R.W.,Hartmann,W.G.,Hedding,R.A.,Kerrigan,P.,Mazumdar, S.,Miller,D.H.,Mysore,P.G.,Nagpal. Adaptive transformer thermal overload protection. IEEE Transactions on Power Delivery.2001

[2]   B.C.,Hagman, W.H.,Kirtley Jr., J.L. Improved transformer top oil temperature model for use in an on-line monitoring and diagnostic system..Hagman,W.H.,Kirtley Jr.,J.L.Lesieutre.IEEE Transactions on Power Delivery.1997

[3]   Tylavsky,D.J.,Qing He,Jennie Si,McCulla,G.A.,Hunt, J.R.Transformer top-oil temperature modeling and simulation.IEEE Transactions on Industry Applications.2000

[4]   Swift,G.,Molinski,T.S.,Lehn W. A fundamental approach to transformer thermal modeling - Part I: Theory and equivalent circuit. IEEE Transactions on Power Delivery . 2001

[5]   Swift, G.Molinski, T.S.,Lehn, W.A fundamental approach to transformer thermal modeling - Part I: Theory and equivalent circuit. IEEE Transactions on Power Delivery . 2001

[6]   Susa, Dejan,Lehtonen, Matti.Dynamic thermal modeling of power transformers: Further development - Part II. IEEE Transactions on Power Delivery . 2006

[7]   IEEE guide for loading mineral-oil-immersed transformers. IEEE. IEEE Std C57.91—1995 . 1996

[8]   Radakovic, Zoran,Feser, Kurt.A new method for the calculation of the hot-spot temperature in power transformers with ONAN cooling. IEEE Transactions on Power Delivery . 2003

[9]   Susa, Dejan,Lehtonen, Matti,Nordman, Hasse.Dynamic thermal modelling of power transformers. IEEE Transactions on Power Delivery . 2005

[10] S Sathiya Keerthi,Chih-Jen Lin.Asymptotic Behaviors of Support Vector Machines with Gaussian Kernel. Neural Computation . 2003

[11] Faiz, Jawad,Sharifian, M.B.B.,Fakhri, A. Two-dimensional finite element thermal modeling of an oil-immersed transformer. European Transactions on Electrical Power . 2008

[12] Swift, G.,Molinski, T.S.,Lehn, W.A fundamental approach to transformer thermal modeling - Part I: Theory and equivalent circuit. IEEE Transactions on Power Delivery . 2001