Transformer winding hot spot temperature prediction based on ε -fuzzy tree

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Abstract. Transformer hot spot temperature is closely related to its operating life, which plays a key role in transformer thermal fault prevention and operational status monitoring. In order to effectively improve the prediction accuracy of the transformer winding hot spot temperature, a method based on ε-fuzzy tree (ε-FT) for predicting winding hot spot temperature is proposed. Taking the 220kV transformer of a substation as the research object, the input and output characteristic variables are extracted through the analysis of relevant mechanisms, which is applied to establish ε-FT model of the transformer winding hot spot temperature, and the proposed method is compared with the other methods. Subsequently, the noise and outliers are added to the modeling data to verify the robustness of the proposed method. The results show that the method can accurately predict the hot spot temperature and resist the bad data in the modeled samples, which has strong generalization ability and robustness.

Key words: Transformer; hot spot temperature; ε-fuzzy tree, prediction, robustness

1. Introduction

Power transformers are important equipment in power systems, directly affecting power supply reliability and condition monitoring of power systems. The hot spot temperature of the transformer winding is one of the main factors determining the insulation performance and service life of the transformer. It plays a key role in the thermal fault prevention, operational life prediction and optimization design of the transformer [1, 2]. Therefore, the study of transformer winding hot spot temperature prediction plays an important role in the safe and stable operation of the power system.

At present, the research methods of transformer hot spot temperature mainly include: hotspot temperature monitoring method based on hardware equipment, hot spot temperature calculation method based on empirical formula, heat path model and numerical calculation, and hot spot temperature prediction method based on artificial intelligence technology. The literature [3,4] developed an online monitoring system for transformer winding temperature based on fiber optic temperature sensor, and achieved certain results. However, this method is costly, and the implantation of sensor devices has an impact on the insulation performance and service life of the transformer [5]. Literature [6-8] uses empirical formulas, thermal path models, and numerical calculations to monitor transformer winding

hot spot temperatures. These methods rely on refined numerical simulation models. With the rapid development of artificial intelligence algorithms, this technology has also been applied to transformer fault diagnosis and hot spot temperature prediction [9-11], and has achieved great research results. In [12], a generalized regression neural network (GRNN) was used to establish a transformer hotspot temperature prediction model, which overcomes the problems in applying BP neural network (BPNN) modeling. Literature [13] uses Kalman filtering algorithm to predict transformer hot spot temperature. Literature [14] uses genetic algorithm to optimize the support vector machine (SVM) parameters to achieve the prediction of transformer hot spot temperature. At present, the research based on artificial intelligence algorithm relies on laboratory simulation data, coupled with the difficulty of determining the hidden layer nodes of neural network algorithm, the determination of SVM parameters and the training time of the algorithm [15], which limits the technology in actual engineering. Applications. Therefore, combined with the actual operating data of the transformer, it is of great significance to study the artificial intelligence method with better performance for transformer hot spot temperature prediction.

The fuzzy tree (FT) method is a tree structure-based adaptive fuzzy inference identification method proposed by Mao Jianqin et al. [16]. This method adaptively divides the modeling information based on the binary tree structure to obtain the corresponding fuzzy subspace. The training and optimization of the parameters of the front and the back in the fuzzy rules simplify the calculation process and solve the "rule explosion" caused by the data "dimensional disaster". Subsequently, in order to improve the ability of this algorithm to resist noise and outliers, the literature [17] proposed a robust ε-fuzzy tree (ε-FT) method. This algorithm inherits the advantages of FT and exhibits stronger robustness, which is suitable for solving high-dimensional nonlinear complex modeling problems. The literature [18, 19] proved that the ε-FT method is better than the BPNN and LSSVM algorithms in regression prediction. Therefore, the author introduces the method into the prediction of the hot spot temperature of the transformer winding for the first time, and has achieved good application. Effect.

In order to improve the prediction accuracy of the hot spot temperature of the transformer winding and the robustness of the prediction model, a prediction method of the winding hot spot temperature based on the A-FT method is proposed. By analyzing the operating mechanism and historical operation data of a 220kV three-winding transformer in a substation, the characteristic variables required for hotspot temperature modeling are extracted, and a hot spot temperature prediction model based on ε-FT method is established. Furthermore, the robustness of the proposed method is verified by adding noise and outliers to the modeling data. Compared with other methods, the proposed hotspot temperature prediction method has higher prediction accuracy and stronger robustness, and exhibits strong generalization ability.

2. ε- fuzzy tree principle

The ε-FT method uses ε-insensitive learning method to calculate the post-parameter parameters of fuzzy rules, which enhances the robustness of the algorithm, and inherits the advantages of short training time, high prediction accuracy and insensitivity to modeling data dimension. It is suitable for solving the modeling problem of high-dimensional complex nonlinear and strongly coupled systems. The specific algorithm steps are as follows:

There are data sets (x, yi), $i = 0,1,\cdots,M$, xi∈Rn, yi∈R, and the maximum number of leaf nodes is L.

Initialize the root node, define $N_1(x) \equiv 1$, and the depth d=1 of the tree. Determine the width α=5 of the fuzzy band and solve the linear parameter c_1 according to equation (1).

$$\min_{c \in R^{(n+1)l}} I(c) = \sum_{i=1}^{M} \left| y_i - c_{\tilde{T}}^T \xi(x_i) \right|_\varepsilon + \frac{\gamma}{2} \tilde{c}^T \tilde{c} \tag{1}$$

Where $\tilde{T}$ is a binary tree set, $t_l \in \tilde{T}$ is a set of leaf nodes, $\tilde{c} = [\tilde{c}_{t1}, \tilde{c}_{t2}, ..., \tilde{c}_{tl}]^T$, $c = [c_{t1}, c_{t2}, ..., c_{tl}]^T$, and $c_{\tilde{T}}^T \xi(x_i)$ are model output values, where the first term is empirical risk, representing the error of the model, the second term represents the complexity of the model, and the parameter is equilibrium. Factor, a compromise between model complexity and training error.

Each node of the current depth d is processed in turn: the node is divided, the membership function on the left and right child nodes is calculated according to equations (2)-(5), and the post-part parameters $c_{\tilde{T}}$ on all leaf nodes are solved according to formula (1).

$$N_1(x) \equiv 1 \tag{2}$$

$$N_t(x) = N_{p(t)}(x)\widehat{N}_t(x) \tag{3}$$

$$\widehat{N}_t(x) = \frac{1}{1 + \exp[-\alpha_t(c_{p(t)}^T \hat{x} - \theta_{p(t)})]} \tag{4}$$

$$\theta_{p(t)} = \sum_{i=1}^{M} N_{p(t)}(x_i)(c_{p(t)}^T \hat{x}_i) \Big/ \sum_{i=1}^{M} N_{p(t)}(x_i) \tag{5}$$

Where: $\widehat{N}_t(x)$ is the auxiliary membership function on the non-root node, $\theta_{p(t)}$ is the data center on the parent node, and $|\alpha_t|$ is the fuzzy band width.

The ε-FT method calculates the output of the divided model corresponding to the input sample as:

$$\hat{y}(x) = \sum_{t_l \in \tilde{T}} \mu_{t_l}(x)(c_{t_l})^T \hat{x} \tag{6}$$

Among them,

$$\mu_{t_l}(x) = N_{t_l}(x) \Big/ \sum_{t_l \in \tilde{T}} N_{t_l}(x) \tag{7}$$

Where $\tilde{T}$ is a binary tree set, $t_l \in \tilde{T}$ is a set of leaf nodes, $c_{t_l} = [c_0^{t_l}, c_1^{t_l}, ..., c_n^{t_l}]^T$ is a linear parameter, N_{t_l} is a fuzzy set defined on the fuzzy subspace, and the corresponding membership function is $N_{t_l}(x)$. If the normalized membership function of $N_{t_l}(x)$ is denoted as $\mu_{t_l}(x)$.

If the root mean square error is less than the root means square error of the output of the pre-partition model, then the partition is saved. Otherwise, the next node of the current layer is processed, and the root mean square error is:

$$RMSE = \sqrt{\sum_{i=1}^{M}(\hat{y}^i - y^i)^2 / M} \tag{8}$$

After the current layer is processed, if the root mean square error of the model output is less than the maximum allowable error or the number of leaf nodes of the current binary tree is greater than L, the algorithm ends; otherwise, let $d = d+1$ continue the algorithm.

3. Hotspot temperature prediction based on fuzzy tree

3.1. Test design

This paper takes a substation 1#220kV oil-immersed transformer as the research object. The transformer was officially put into operation in 2017, and the manufacturer is TBEA Hengyang Transformer Co., Ltd. According to the relevant literature [12-14, 20] and the experience of the inspection personnel, the variables affecting the hot spot temperature of the transformer winding are: oil temperature, power loss, load current, power factor, ambient temperature and wind speed. Considering the data acquisition situation of most substations and the generalization of the proposed method, the top temperature, active power loss and load current are used as input variables to establish the -FT model of the transformer hot spot temperature. The hot spot temperature is the measured transformer winding temperature. The model structure is shown in Figure 1. Collect 120 sets of historical operation data of the transformer with a time interval of 30 min. The first 100 sets of data are used as training samples, and the last 20 sets of data are used as test samples. Part of the modeling data is shown in Table 1:
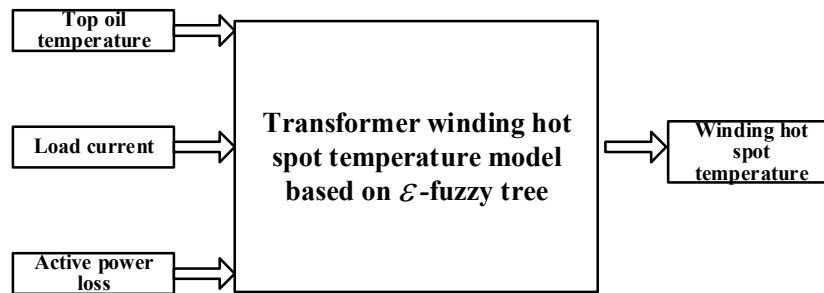

Figure 1. The prediction model structure of transformer hot spot temperature.

In order to measure the accuracy of the algorithm modeling involved in the paper, the root mean square error is used for comparison. The expression is as follows:

$$R_{MSE} = \sqrt{\sum_{i=1}^{N}(T_i - T_{io})^2 / N} \tag{9}$$

Where N is the number of samples; T_i is the predicted value of the winding hot spot temperature model; T_{io} is the measured value of the winding hot spot temperature.

Table 1. The partial transformer historical operation data.

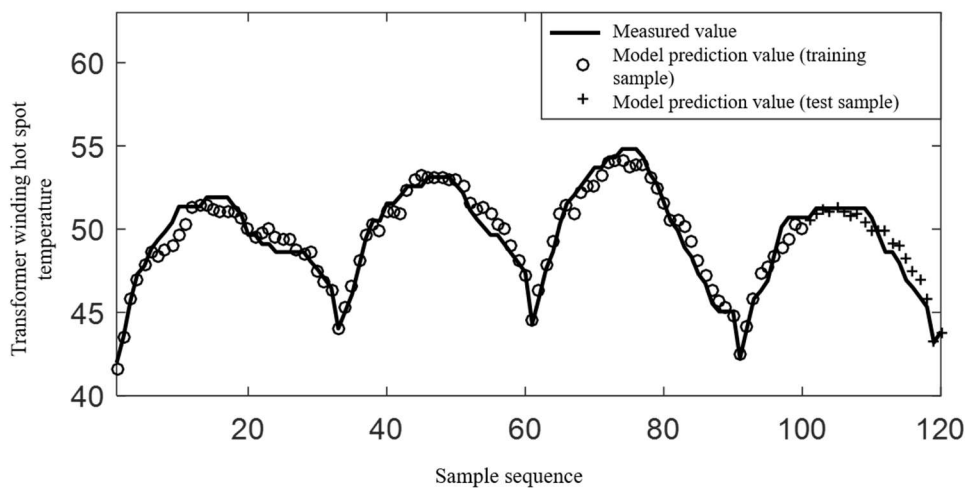| Serial number	Top oil temperature / °C	Load current /A	Active power loss / MW	Hot spot temperature / °C
1	40.509	174.772	0.6	41.971
2	41.559	186.744	0.3	43.565
…	…	…	…	…
30	46.078	182.324	0.8	47.596
31	46.078	170.088	0.5	47.034
				…
…	…	…	…	
61	41.934	197.31	0.3	44.306
62	42.9	208.873	0.1	45.909
…	…	…	…	…
91	40.612	184.49	0.3	42.253
92	41.728	197.569	0.8	44.043
…	…	…	…	…

3.2. Modeling effect

Figure 2. The modeling effect of hot spot temperature.

Figure 2 shows the modeling effect of the transformer winding hot spot temperature. It can be seen from the figure that the ε-FT based hotspot temperature prediction method for training samples and test samples can accurately predict the hot spot temperature, and the root mean square error is 0.6424 ° C and 0.6572 ° C, respectively. Estimate accuracy and strong generalization capabilities. In addition, the method uses about 100s in training model, and adopts 100 sets of samples rolling training, which can be applied online and has high engineering application value.

In this paper, the ε-FT based transformer hotspot prediction method is compared with the prediction methods based on FT, BPNN and LSSVM. The error results are shown in Table 2. Among them, the square root error of the training sample is recorded as PRMSE; the root mean square error of the test sample is recorded as QRMSE. It can be seen that the hot spot temperature prediction method based on ε-FT is smaller than the root means square error of the test sample, the prediction accuracy is higher, and the generalization ability is stronger, which is better than the hot spot temperature prediction method based on FT, BPNN and LSSVM. Considering that the proposed method uses fewer training samples, the training time of several methods is not much different, both less than 0.5s. No detailed comparison is made here, but the penalty factor and kernel function parameters in the LSSVM algorithm are more

time-consuming. Long, the text uses genetic algorithm to determine the parameters, the parameters are 160.1935, 0.8679.

Table 2. Comparison of different modeling methods.

	FT	ε -FT	LSSVM	BPNN
P_{RMSE}/°C	0.4498	0.6424	0.5636	0.7907
Q_{RMSE}/°C	0.8820	0.6572	0.7098	0.9700

4. Hot spot temperature prediction method robustness verification

Due to equipment aging, electromagnetic interference and human factors, the measurement data at the engineering site often contains data noise and outliers. If these bad data cannot be effectively identified and resisted, it will affect the prediction of the hot spot temperature of the transformer winding. Therefore, the temperature of the transformer hot spot is studied. The robustness of the prediction method is very important. In order to verify that the hotspot temperature prediction method proposed in the paper has the ability to resist noise and outliers, random noise with a signal-to-noise ratio of 25 and five outliers are added to the training samples. Then, based on the above data, a prediction model of the transformer hot spot temperature is established. The modeling effect is shown in Figure 3. It can be seen from the figure that the hotspot prediction method proposed in this paper is less affected by noise and outliers. The error precision is equivalent in both cases. The modeling errors of training samples and test samples are 0.7115 °C and 0.7249 °C, respectively. Compared with the noise and outliers, the root mean square error is only increased by 0.0691 °C and 0.0677 °C, which indicates that the proposed method can effectively resist the noise and outliers in the modeled samples and has strong robustness.
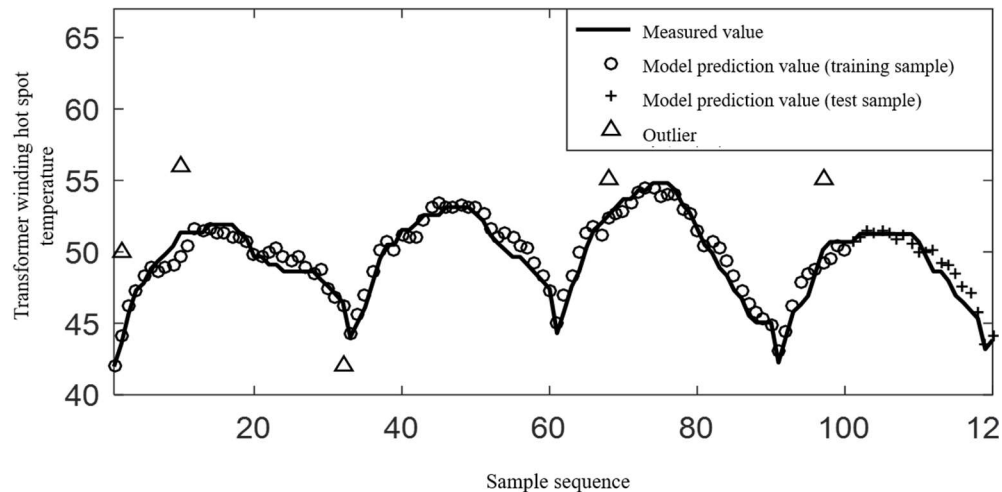

Figure 3. The robustness display of hot spot temperature prediction method.

In order to fully explain the advantages and disadvantages of the four methods involved in the hot spot temperature prediction application, the FT, BPNN and LSSVM models of hotspot temperature are established based on samples with noise and outliers. A comparison of the modeling errors for the test samples is shown in Figure 4. It can be seen from the figure that when modeling based on samples that also contain bad data, the proposed method is almost immune to noise and outliers, while the prediction errors of the other three methods increase significantly. Therefore, from this point of view, it also fully demonstrates that the proposed method has higher prediction accuracy, stronger generalization ability and robustness than the other three methods.
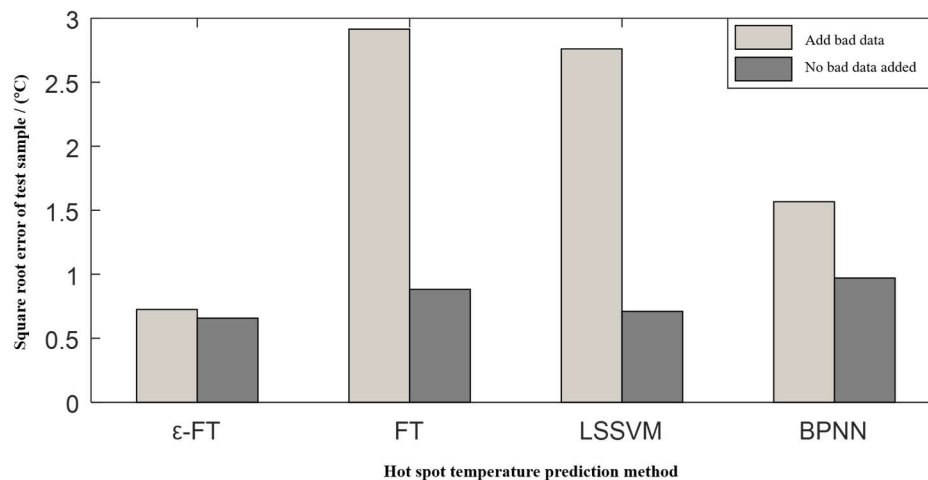
Figure 4. The robustness comparison of hot spot temperature prediction method.

5. Conclusion

In this paper, a method for predicting hot spot temperature of transformer windings with high prediction accuracy and robustness is proposed. The main conclusions are as follows:

1) The ε-fuzzy tree method can deal with the complex modeling problem of nonlinearity in transformer hot spot temperature. Compared with FT, BPNN and LSSVM, it has higher prediction accuracy and stronger generalization ability.

2) The proposed ε-FT based transformer hot spot temperature prediction method can effectively identify and resist noise and outliers in the modeling data, and has strong robustness.

3) The proposed ε-FT based transformer hot spot temperature prediction method uses the actual running history data of the transformer to verify, which is closer to the actual application effect and has strong engineering application value.

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