RESEARCH ON INTELLIGENT DIAGNOSIS METHOD OF OIL TEMPERATURE DEFECT IN DISTRIBUTION TRANSFORMER BASED ON MACHINE LEARNING

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ABSTRACT

Long-time operation under abnormal oil temperature is one of the critical factors causing short service life and limit capacity of distribution transformers, and even tripping accident due to insulator failure. At present, only a simple static alarm function is available to detect the over-limit of oil temperature in distribution transformer. This function cannot disclose the defect evolvement. A prior alarm function to early identify abnormal oil temperature is needed in order to stop the development of defects. This paper introduces a novel intelligent prediction method based on machine learning methods for real-time abnormal oil temperature detection. This method establishes a dynamic association learning model using decision forests algorithm to predict oil temperatures based on transformer parameter, power load, as well as weather condition under the normal operation state. Comparing the predicted oil temperature with online measurement, we can find the abnormal oil temperature state and develop prior alarm function to detect the defect of distribution transformer. The decision making procedure based on this method has been applied into distribution transformers of Shanghai. The results validate the accuracy of the method and show efficiency when applying on the maintenance planning of distribution transformer.

Keywords: decision tree; machine learning; prior alarm; oil temperature; distribution transformer.

INTRODUCTION

Oil-immersed transformer is the core component of power distribution system[1]. The excessive oil temperature is mainly caused by insulation damage of metal parts, winding inter-turn short circuit, transformer overload, and transformer cooling system failure, etc. Long time operation under abnormal oil temperature would lead to transmission efficiency reduction and breakdown accidents, and finally shorten the life time of transformer[2][3][4].

There are two traditional methodologies to identify abnormal oil temperature, which are online and offline separately. Online method, commonly used in the existing EMS, has simple static alarm function which gives alarm signal when the measurement exceeds the limit, therefore it lacks the ability of prior anomaly detection. Offline method, relying on thermal field model[5] or infrared imager[6], is complicated and not feasible for the real-time decision making[7][8].

The existing online method could not send the alarm signal in advance, which will allow the defects to develop a while inside the transformer until temperature reaches to the limit. It finally endangers the power grid or increases the maintenance cost once the defects lead to transformer failure or tripping.

The massive data of distribution transformers provide a rich multi-source heterogeneous database for the operation and management of distribution networks. In order to solve the above problems, a new oil temperature anomaly detection algorithm is developed by introducing decision tree algorithm, a machine learning method as we know. The algorithm simulates the relationship between the oil temperature and other related attributes, such as loading level, current, voltage, winding temperature and meteorological data and so on. The predicted oil temperature can be given and used for the defect decision process by comparing with the measurement. As a result, the online prior alarm can be given for the engineer to take action in advance.

A NEW METHODOLOGY OF OIL TEMPERATURE PREDICTION BASED ON DECISION TREE ALGORITHM

The selection of machine learning method

Decision tree[9][10][11] algorithm has many advantages comparing with other machine learning methods as following:

1) Compared with linear regression algorithm, it can deal with the non-linear relationship, and has strong robustness to outliers.
2) Compared with in-depth learning, decision tree parameter adjustment is simple and the training time is relatively short. The predicted results are also interpretable.
3) Compared with support vector machine, it has better tolerance for data imbalance problem, and can also reduce the risk of over-fitting through integration.

Based on the above characters, we select the decision tree algorithm to do the analysis in this paper. In order to improve the accuracy, we utilize an integrated algorithm composed of multiple trees to achieve the capability of interference and over-fit prevention.

Decision tree algorithm based on Information Entropy Theory (IET)

IET is established by C. E. Shannon to solve the problem of information transmission (communication) process and also known as statistical communication theory[12][13][14]. IET is utilized here to decide the critical node for each step of decision tree algorithm.

Let IS be the oil temperature historical data set. $|IS|$ represents the number of samples in the historical data set. IS can be divided into subsets, $U_1, U_2, \cdots U_q$, according to different oil temperatures. $|U_i|$ indicates the number of samples of U_i. There are n related attributes, expressed as $A_1, A_2, A_2, \cdots A_n$. The number of the value of the attribute A_k is m, indicated as $V_1, V_2, V_2, \cdots V_m$. For each A_k, U_{ij} represents the subset of U_i where the value of A_k equals to V_j . Some definitions are given as bellow:

1) Probability of U_i in IS: $P(U_i) = |U_i|/|IS|$
2) Conditional probability of U_{ij}:$P(U_i/V_j) = |U_{ij}|/|U_i|$
3) $H(U) = \sum_{i=1}^{q} P(U_i)\, log \frac{1}{P(U_i)}$, which is the prior entropy showing the average certainty regarding oil temperature category. $H(U) = 0$ represents q equals to 1 and means no uncertainty. If all $P(U_i) = 1/q$, which shows the maximum of uncertainty.
4) $H(U|A_k) = \sum_{j=1}^{m} P(V_j) \sum_{i=1}^{q} P(U_i|V_j)\, log \frac{1}{P(U_i|V_j)}$, which is the posteriori entropy showing the average uncertainty of the oil temperature category for the attributeA_k.
5) $I(U, A_k) = H(U) - H(U|A_k)$, which is the mutual information giving the degree of reduction in the average uncertainty of the oil temperature category for each attribute A_k.

It can be seen that the prior entropy and the posterior entropy describe the average uncertainty, and mutual information is the reduction of uncertainty. The bigger of the value of mutual information, the higher of the weight of attributes. This character is used to select the major attribute as tree node.

The following steps gives the detail of decision tree algorithm based on mutual information:

Step 1. Calculate the mutual information of each attribute A_k for IS;

Step 2. Select the attribute A_k which has the largest mutual information.

Step 3. The subsets can be obtained based on the values of A_k;

Step 4. For each subset, we implement same procedure as above steps to build a tree. If the subset shows no uncertainty of oil temperature category, the corresponding branch is ended with oil temperature U_i.

After the decision tree is built, each leaf node is the oil temperature category, and each common node corresponds to the attributes which represent operation conditions. The oil temperature can be estimated from the decision tree by checking the root node to the leaf node.

Decision forest[15][16] algorithm based on BAB (Bootstrap aggregating Bagging)

Decision tree algorithm has the advantages as simple structure and fast construction. However, it could lead to over-fitting, or small changes in data may lead to large difference of the decision tree. In order to solve these problems, we further use the decision forest[7,8] model by applying the idea of integration. The decision forest model adopts BAB decision strategy. Each decision tree in the forest selects different data from the original training set. The final prediction results are determined by the voting results of each tree. Results shows that the decision forest avoids the disadvantages of a single decision tree.

AN EXAMPLE OF DECISION TREE ALGORITHM

For better understanding of the decision tree algorithm, we give a simple example here, where we assume that oil temperature (OT, ℃) is related to the four attributes: active power (AP, MW), ambient temperature (AT,℃), current (C, A), and winding temperature (WT,℃). The data set is shown in table 1, and we can get the value of q, k as 2 and 4 separately.

Table 1: Oil Temperature Data Set (IS).

NO	AP	AT	C	WT	OT
1	100	20	80	30	30
2	100	20	80	40	30
3	90	20	80	30	40
4	80	25	80	30	40
5	80	30	70	30	40
6	80	30	70	40	30
7	90	30	70	40	40
8	100	25	80	30	30
9	100	30	70	30	40
10	80	25	70	30	40
11	100	25	70	40	40
12	90	25	80	40	40
13	90	20	70	30	40
14	80	20	80	40	30

Firstly, we can get the prior entropy H (OT) = 0.94 based on the above data set . The posterior entropy and mutual information are shown in the table2.

Table 2: Entropy and Mutual Information Result

	Posteriori Entropy	Mutual Information
AP	0.694	0.246
AT	0.911	0.029
C	0.789	0.151
WT	0.892	0.048

We can see the mutual information of AP in IS is the largest one, which means that active power will be selected as the tree root, and three subsets IS1, IS2, IS3 will be constructed according to the three values of active power. After all steps are completed, the final matching decision tree can be shown in Figure 1 below.

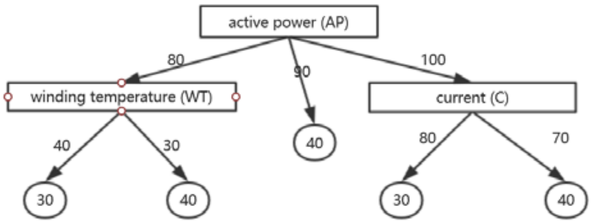

Figure 1 Decision Tree Diagram

ALGORITHM ACCURACY ANALYSIS

This paper simulates 29 transformers in Shanghai grid from July 2016 to September 2017. The relevant attributes include active power, inactive power, current, voltage, winding temperature, and ambient temperature of each transformer.

We give the detail data of transform 9th at two days (Spring13 and July 25) regarding two typical demand levels respectively, as shown in Figure 2 and Figure 3. It can be seen that the predicted oil temperature given by the algorithm can well fit the actual oil temperature.

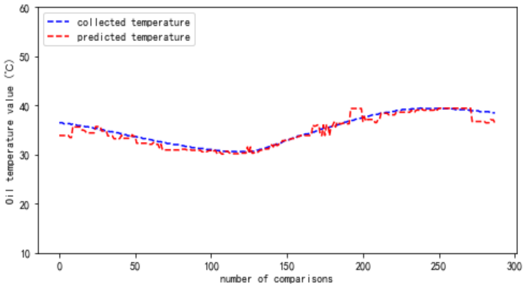

Figure 2 Prediction result for transformer 9th, Spring 13

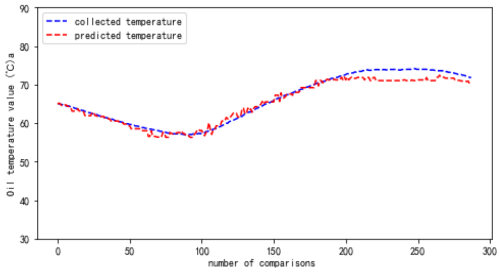

Figure 3 Prediction result for transformer 9th, July 25

Furthermore, we give the average prediction deviation ratio (DR) for each transformer in Figure 4. It is concluded that the prediction result is acceptable since the DR of most transformers is around 5%.

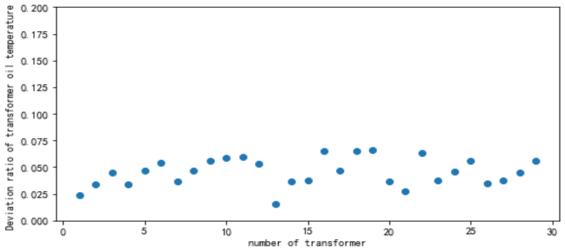

Figure 4 The deviation ratio (DR) of each transformer

With the defect develops, the DR will getting bigger. We can use linear curve to fit the DR curve, and the slope can be used as a basis to decide the abnormal state of transformer. Figure 5 gives a linear fitting curve for transformer 9th in one year, and the slope of this curve is 0.001 which means transformer is under a normal state.

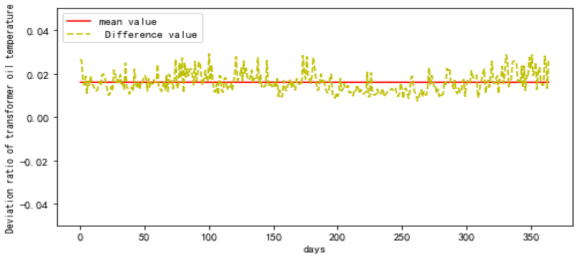

Figure 5 DR linear fitting curve in one year

THE STATE ONLINE DECISON MAKING PROCEDURE BASED ON DECISION FOREST ALGORITHM

We assume that T1 represents the measurement of oil temperature, T2 represents the predicted oil temperature, ΔT represents the deviation of the above two, the slope of DR linear fitting line is K. ΔTmax, T1max is the maximum value of ΔT, T1. For the decision making, we introduce three alarm indicators: γ, λ and η, which correspond to limit setting of the temperature , ΔT and K respectively and can be given based on the critical level of the transformer. The decision criterion for transformer state is given as below:

1) Normal operation state: ΔTmax< λ , K<η, T1max<γ;
2) The prior alarm state: ΔTmax> λ or K>η, T1max<γ;
3) The critical alarm state: T1max>γ.

We use the decision forest tree to get the predicted oil temperatures from Oct, 2017 to present for 29 transformers. Applying the above criterion by using the same limit value as γ=90, λ =15 and η=0.02. The maximal T1 value, maximal deviation and slope of DR linear fitting curve are shown in Figure 6,7,8 respectively. Since the maximal temperature values of all transformers are less than γ, it means no transformer reaches state 3. However, Figure 7 Figure 8 shows that for transformer 28th, ΔTmax> λ , K>η, which means transformer 28th is at state 2 while the rest are at state1. We may start to pay attention to the operation of transformer 28th right away.

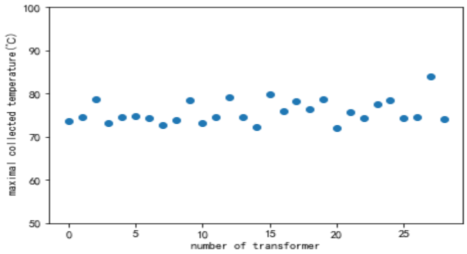

Figure 6 The maximal T1 value of each transformer

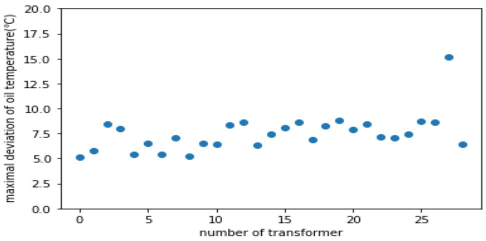

Figure 7 The maximal deviation of each transformer

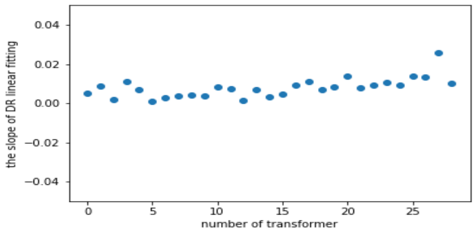

Figure 8 The slope of DR linear fitting curve of each transformer

CONCLUSION

The online intelligent diagnosis of oil temperature defect of transformer based on decision tree algorithm is provided, where information entropy theory is used for tree node selection. It is an innovation and promotion of current oil temperature anomaly detection methods. By using machine learning method to process and analyze large data, the algorithm model can be self-optimized. It provides prior alarm to prevent the defect development of distribution transformer, finally reduces the possibility of tripping or damage of transformer. The testing for 29 transformers shows that the algorithm is accurate and decision making method is feasible for the online application.

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