Application of Optimization Technology for Overhaul Decision of Substation Equipment Based on Machine Learning

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Abstract. With the continuous improvement of living standards and the continuous increase of electricity load, the number of power transmission and transformation equipment also increases rapidly. The original maintenance mode is not enough to guarantee the safe operation of the huge power grid. This paper mainly studies the research and application of machine learning based maintenance decision optimization technology for substation equipment. Starting from the technical principles of online monitoring and condition maintenance of substation equipment, this paper has realized an intelligent monitoring and maintenance early warning system combined with deep learning model. The main functions of this system include monitoring device management, operation monitoring and comprehensive display, etc., which can effectively carry out online monitoring and state early warning of substation equipment. It greatly improves the intelligent degree of operation and management of substation equipment, saves the cost of traditional manual monitoring, and effectively prevents the economic loss caused by substation equipment failure, which has far-reaching significance for promoting the construction of smart power grid.

Keywords: Machine Learning, Substation Equipment, Anomaly Detection, Trouble Shooting

1. Introduction
Vigorously promote the informationization construction in recent years, with the power grid, smart grid information platform of highway construction, the new technology the role in the field of information technology in traditional electric power is more and more big, the smart grid and data grid has become a development trend of the future, the explosive growth of the electric power big data is becoming more and more attention in the field of industrial production and scientific research and attention. The informationized power system produces large scale, many types and fast changing big data all the time and everywhere, which provides a rich data source for relevant data analysis and research. Some relatively mature machine learning algorithms have been widely used in data analysis in various fields, and may also be a hot research direction in the future for a long time [1-2]. Due to
the explosive growth of current power grid data and the endless emergence of various sensors, capacitive equipment has a large amount of data, complex data characteristics and uneven data quality, so it is difficult to obtain ideal results directly by using traditional statistical methods. How to improve the traditional statistical methods to develop more universal and generalizable models, how to select appropriate machine learning algorithms to analyze large-scale data, and how to improve the existing machine learning algorithms to improve the effect of the model are all problems that need further research.

The early warning about the maintenance of substation equipment at home and abroad is mainly online monitoring. The equipment is in normal operation, and the test method of monitoring under the operating voltage is called online monitoring. The United States, Japan, Australia and other countries have also developed the corresponding capacitive equipment online monitoring equipment. The indicators monitored mainly include dielectric loss tan δ, current value I and capacitance value C, through which defects in the early stage of the equipment can be identified [3]. The principle of digital measurement is to measure the voltage and current signals from the high voltage bus end to the low voltage equipment end, so as to get the value of dielectric loss. The monitoring device for dielectric loss value of current transformer and transformer bushing developed in Australia can display the real-time numerical monitoring results. It uses a high-speed counter to measure the phase difference between the measured signal and the standard sinusoidal signal, with a resolution of 0.14mrad [4].

In this paper, the current running condition of the substation equipment is analyzed, and the problems in the maintenance process of the chicken substation equipment are analyzed. Finally, the necessity and feasibility of the state maintenance of the substation equipment are put forward.

2. Construction of diagnostic model of substation equipment
Failure prediction.

(1) PCA test.
When PCA is used for anomaly detection, the main idea is to find outliers that violate data correlation by adopting the idea of principal component analysis. The main method is to map the original data from the original space to the principal component space, and then map the projection back to the original space. For most data, if only the first principal component is used for mapping and reconstruction, the error after reconstruction will be small, while for outliers, the error will still be relatively large after reconstruction [5-6].

Let D be a data set of D dimensions with N samples and the covariance matrix of the data set is \( \Sigma \). Its covariance matrix can be diagonalized.

\[
\Sigma = \mathbf{P} \Delta \mathbf{P}^T
\]  

(1)

Where is an orthogonal matrix of dimension (d,d), with eigenvectors with \( \Sigma \) in each column. \( \Delta \) is a diagonal matrix \( \Delta (d \times d) \). In two dimensions, an eigenvector can be viewed as a line, and when you're in higher dimensions, you can look at a hyperplane. Characteristic value of the diagonal matrix A, from big to small order, every column corresponding eigenvector matrix \( \mathbf{P} \) also adjust, first I let \( \mathbf{P} \) for \( \Delta \) value of the ith A diagonal.

The projection of data set D in principal component space is as follows:

\[
Y = \mathbf{D} \times \mathbf{P}
\]  

(2)

Note that you can only project on a partial dimension. If you are using a top-j principal component, then the projected dataset is

\[
Y^j = \mathbf{D} \times \mathbf{P}^j
\]  

(3)

The outlier score of data \( \mathbf{D}_i \) can be defined as follows:

\[
\text{Score}(\mathbf{D}_i) = \sum_{j=1}^{d} (||\mathbf{D}_i - \mathbf{R}_j^j||) \times \text{ev}(j)
\]  

(4)
Notice $||\text{Di-Rji}||$ refers to the Euclidean norm, $\text{ev (j)}$ said the principal component at the Top - $j$ accounted for the proportion of all principal components, and because the characteristic value was sorted from big to small. According to the properties of principal component analysis, the deviation of outliers will be larger in the final principal component, and outliers will have a higher anomaly score [7].

(2) Vector Machine Detection.

A class of support vector machines (SVM) can be seen as variants of linear and logistic regression models in which edge concepts are used to avoid overfitting, just as regularization is used in regression models [8].

Support Vector Machine (SVM), as a successful algorithm, has been widely used in engineering because of its excellent generalization ability. One-class SVM can be seen as a variant of linear model and Logistic regression model, in which the concept of boundaries is used to avoid overfitting, just as regularization is used in regression model [9]. These error penalties are calculated using the concept of relaxation variables. Although it is possible to use square loss (such as regression), it is common to use other forms of loss function (such as hinge loss) in support vector machines. The main problem of using support vector machines to detect outliers is that the model mainly needs to separate the two classes with decision boundaries. However, in outlier detection, the data is not marked, so assume that all provided examples belong to normal classes, and then construct the model.

Maintenance Algorithm Based on Fault Prediction

SVM algorithm is a commonly used algorithm foundation in the field of machine learning. It has strong generalization performance and can be used for regression prediction and classification tasks. The main operating mechanism of the algorithm is to map the samples to the high latitude feature space and use different algorithm kernel functions to distinguish the feature samples in such space. Sample types can be classified by dividing a soft interval domain [10].

By analyzing the operating basis of the algorithm, we can roughly find that the SVM algorithm divides the sample space through different types of kernel functions. But there is often more than one line or hyperplane dividing the sample space. Therefore, the SVM algorithm outputs the optimal parameter by averaging the distances between the hyperplane and the two types of sample Spaces. The continuous training of the SVM algorithm is to find the relevant parameters that can fit the linear hyperplane. For different types of data, we often choose different types of hyperparameters when we choose the training SVM algorithm model. For example, when the number of features in our data set is much larger than the number of sample data, we will choose the linear kernel function. When linear kernel function is used for dichotomy problem, sigmoid activation function is often used. On the contrary, if the number of features is less than the number of samples, we can choose the radial basis kernel function as the classification function. Often the selection of these types of kernel functions should not only be selected through theoretical significance, but also need to be selected by experimental comparison in practical application.

We will focus on the linear kernel because this is the SVM kernel that will be used in this chapter. The linear kernel function usually adopts the formula $y=kx+b$ as the linear formula. The goal is to find the feature sample space that this line can be divided into.

Suppose that the characteristics of a batch of transformer data types are dots and crosses, and its characteristic dimension is assumed to be two-dimensional. It can be represented visually through two-bit coordinates, and we need to find a straight line in this two-dimensional plane to separate the two characteristic data. And these simple $y=kx+b$ lines are what we call "hyperplanes that divide samples." But for the classification of this hypothetical sample we set the classification function as $F(x)=W^T X + B$, and in fact $W$ is the transpose of the system $K$. The purpose is to make $W$ applicable to eigenvectors of higher dimensions. For the two types of data to be classified, we set their labels as -1 and +1 respectively. When the value of the data with the sample of 1 is greater than $f(x)$ after the input of the feature, and the value of the data with the sample of -1 is less than $f(x)$ after the input of the feature, then we task that the classification line has been found. However, there are often many classification lines. How to select the optimal classification line? We use the average distance between
two sample points and the line as the selection criterion for the optimal line. By constantly looking for
the line, so that the classification effect to achieve the best.

3. Fault prediction algorithm test of overhaul system of substation equipment

3.1. Algorithm test
In this paper, 7312 sample data of A transformer in substation A were collected on a daily basis. The
first 6000 data were taken as the training samples of the model, and the last 1312 data samples were
taken as the test samples of our model.

Among them, partial discharge or damp, low energy discharge, low temperature overheating,
medium temperature overheating will reach the preliminary warning state, it needs the relevant
departments on the line timely maintenance. We first matched the monitoring data of the previous day
with the labels of the next day one by one (to predict the status of the next day for timely maintenance
and repair). Then, the first 6000 data were input into our model for training iteration. Mean_squared_error was selected as the loss function value of the model, and the trend graph of the
number of model iterations and the loss function value was observed.

In order to compare the performance of the proposed model in transformer monitoring, the BP
neural network and LSTM models were trained and tuned on the above divided training set and test set
respectively. After running on the data set for many times, the evaluation results were taken as the
evaluation criteria. Finally, more detailed comprehensive measurement indexes such as P, R and F are
obtained for each model.

3.2. Performance test of maintenance system
System environment Win7 +MySQL hardware system environment requirements: 8G memory, 1000G
hard disk.

4. Test result

4.1. Failure prediction

As shown in figure 1, by comparison with the experimental findings: in this paper, the basis of deep
study the classification of the model has good prediction results, than traditional machine learning
model LSTM rose 5% on the whole, this paper puts forward the basis of deep learning model in the

![Figure 1. Comparison of model results](image-url)
study of three types of transformer data can have stronger learning abilities, namely the three types of monitoring data can be found in the perception of transformer faults are the most sensitive data, can improve the prediction accuracy and efficiency of transformer fault type.

With the continuous update and innovation of substation equipment monitoring technology, more substation monitoring devices will be applied to substation monitoring. How to make use of more complex comprehensive characteristic data is an important guarantee for the prediction model to achieve accurate prediction. In view of the use of monitoring data generated by three different types of substation monitoring equipment, we have carried out a meaningful exploration and research for the prediction of substation equipment with multiple data types as input. Moreover, the proposed method can be applied to input of different data types.

4.2. Maintenance system testing

Table 1. Maintenance system performance test

|                      | 20      | 50      | 100     | 200     |
|----------------------|---------|---------|---------|---------|
| Mean response time(s)| 0.317   | 1.58    | 1.49    | 2.07    |
| Maximum response     | 0.47    | 2.21    | 2.54    | 4.19    |
| time(s)              |         |         |         |         |
| Transactions per second | 1.35   | 6.34    | 6.87    | 10.16   |
| Clicks per second    | 21.89   | 107.54  | 113.92  | 118.26  |

Figure 2. Maintenance system performance test

As shown in table 1 and figure 2, is to build local area net, we do not test, respectively, the number of customers access to use the system at the same time, system to the corresponding time, judging from the simulation, when there are 200 users access and click on the same document at the same time, the things that the average response time of 4.2 seconds, the test results can be fully shows that the system can be put into operation in late after meet the demand of electric power enterprises the use of the system.

5. Conclusion

Today, with the rapid development of modernization, the online monitoring and maintenance system of the corresponding substation has been able to achieve relatively mature applications, and the applications in some fields have brought better economic benefits to this field. In order to be able to meet the needs of substation workers and the substation equipment on-line monitoring and
maintenance of the specific implementation, we research and analysis of the online technology, substation and effectively combined with the corresponding monitoring data for the substation equipment condition monitoring and early warning, and deep learning technology is introduced into the field, realize more intelligent online monitoring and maintenance. In general, the completion of the system and the paper is preliminarily perfected and realized in strict accordance with the predetermined plan, but there will be some problems due to the limitation of its level more or less.

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References
[1] Tammy, Lapeyrouse, Chan, et al. Interoperability Testing of Substation Equipment[J]. Transmission & Distribution World: The Information Leader Serving the Worldwide Power-Delivery Industry, 2016, 68(1):50-52,54-55.
[2] Baghmisheh A G, Estekanchi H E. Effects of rigid bus conductors on seismic fragility of electrical substation equipment[J]. Soil Dynamics and Earthquake Engineering, 2019, 125(Oct.):105733.1-105733.16.
[3] Krieg T, Finn J. [CIGRE Green Books] Substations || Innovation and Standardization of Substation Equipment[J]. 2019, 10.1007/978-3-319-49574-3(Chapter 9):123-140.
[4] Yaakov R, Arie S. COMBINED OVERHAUL AND REPLACEMENT POLICIES FOR DETERIORATING EQUIPMENT[J]. Journal of the Operations Research Society of Japan, 2017, 21(2):274-286.
[5] Yang L, Wei R, Shen H. The fractal characteristic of facial anthropometric data for developing PCA fit test panels for youth born in central China[J]. Journal of Occupational & Environmental Hygiene, 2017, 14(1):9-16.
[6] Pang S T, Chang Y H, Lin P H, et al. Prospective clinical study of a prostate cancer (PCa) rule-out blood test for PSA gray zone patients using a sensitive circulating tumor cell assay.[J]. Journal of Clinical Oncology, 2018, 36(6_suppl):143-143.
[7] Yang Z M, Wu H J, Li C N, et al. Least squares recursive projection twin support vector machine for classification[J]. International Journal of Machine Learning and Cybernetics, 2016, 7(3):411-426.
[8] Tharwat A, Hassani A E, Elnaghi B E. A BA-based algorithm for parameter optimization of Support Vector Machine[J]. Pattern Recognition Letters, 2017, 93(jul.1):13-22.
[9] Han S J, Bae K Y, Park H S, et al. Solar Power Prediction Based on Satellite Images and Support Vector Machine[J]. IEEE Transactions on Sustainable Energy, 2016, 7(3):1255-1263.
[10] Geranian H, Tabatabaei S H, Asadi H H, et al. Application of Discriminant Analysis and Support Vector Machine in Mapping Gold Potential Areas for Further Drilling in the Sari-Gunay Gold Deposit, NW Iran[J]. Natural Resources Research, 2016, 25(2):145-159.