A Power Metering Pipeline Fault Warning Method Based on Deep Learning

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ABSTRACT: With the continuous deepening of the informationization and intelligentization of the electric power industry in China, the fault early warning and diagnosis system of the electric power verification system in China reflects the current situation of insufficient intelligentization. Traditional fault diagnosis system collects operation data of verification system through sensor network, acquisition network and log message technology, and then carries out manual or semi-manual fault detection and processing. There is a small amount of data collected, and the traditional data mining methods such as expert judgment method, decision tree method and SDG model have low efficiency and poor diagnosis effect. In view of this situation, this paper introduces deep learning technology into the verification system of automated pipeline, realizes the integration of fault early warning and diagnosis, builds a fault classification model for automated pipeline based on deep learning neural network, and tests and verifies the effect of model early warning with actual system operation data. The validation of the algorithm gives the result of fault early warning in the form of probability, fully considers the factors affecting the interaction between the pipeline and equipment, has a better effect of fault early warning provides more accurate reference for fault detection and prevention of automated pipeline.

1. Introduction

With the prominent development of China's energy industry, especially the power industry, the scale of power grid is expanding, and the demand for intelligent metering equipment is increasing. Automation, standardization, process and development towards intelligentization of power metering and verification is a clear construction requirement put forward by power enterprises under the construction and deployment of smart grid. A key link of the automatic verification system is that it can give an intelligent early warning to the faults of the verification pipeline system, notify and carry out comprehensive fault prevention and investigation measures, so as to prevent the faults of the automatic verification pipeline from happening. Based on the existing research in the field of fault early warning, artificial intelligence technology is increasingly and widely used in various fault early warning scenarios, and has achieved good performance.[1]

However, for the target scenario discussed in this paper, the verification automation pipeline only began to be widely used in the country in the past two years, so the accumulated diachronic running data is less, which can be used as the database for the algorithm research of rule classification is more scarce. Therefore, it is difficult to use the technical methods for big data analysis, and it is impossible to obtain mature and available expert diagnosis system. At the same time, in the metering pipeline, the equipment interacts with each other. Most of the fault early warning systems of existing manufacturers are specific early warning for single hardware components. They do not synthetically analyze the operation of the
whole pipeline, and the lack of consideration for the mutual influence factors among the equipment, resulting in the lack of the overall fault early warning method.

In view of the shortcomings of the fault early warning system of verification pipeline system, this paper proposes a power metering pipeline fault warning method based on deep learning. Firstly, a neural network model for fault classification is built. And based on the existing data foundations, a clear fault classification data is selected as the sample data set, and the neural network model is supervised and trained. Finally, the clear fault data is used to verify the performance of the trained algorithm model. Experiments show that the algorithm model has strong learning ability and stability, and can eventually realize the probability of early warning for different types faults with high accuracy. It can provide scientific fault detection advice for the staff of the verification system.

2. Deep Learning Technology Based on Stacked Automatic Encoder

Deep learning can be regarded as a neural network of multi-layer hidden layer, that is, through data initialization and feature extraction, to locate the intrinsic attributes of the original data set, so as to achieve the goal of scientific and reasonable classification and analysis. At present, the main deep learning methods include Stacked Automatic Encoder (SAE), Restricted Boltzmann Machine (RBM), Convolutional Neural Network (CNN) and so on.\(^3\)

Stacked Automatic Encoder (SAE) can effectively extract the intrinsic characteristics of the original data set, which is stacked by its basic unit Automatic Encoder (AE). A basic AE can be regarded as a three-layer neural network, in which the output layer has the same size as the input layer, and the structure is shown in the following figure. Set the input data set \(X\) to the input layer. The process from the input layer to the hidden layer is called coding, and is completed by the encoding function \(F\). The process from the hidden layer to the output layer is called decoding, and is completed by the decoding function \(G\). Finally the output data set \(Y\) is obtained.

![Figure 1: Figure of SAE network](image)

| Layer | Description |
|-------|-------------|
| X Layer | Input layer |
| F Layer | Encoding function |
| H Layer | Hidden layer |
| G Layer | Decoding function |
| Y Layer | Output layer |

The operation process of the encoding and decoding process of the Automatic Encoder can be expressed as:
\[ H = F(X) = S(WX + P) \]  
\[ Y = G(H) = S^{-1}(W^TX + Q) \]

(1) \hspace{1cm} (2)

S(x) is sigmoid function, \[ S(x) = \frac{1}{1 + e^{-x}} \]; \[ S^{-1}(x) = e^{-x}(1 + e^x)^{-2} = S(x)(1 - S(x)) \]; W is the weight data set of the encoding process from the input layer to the hidden layer. \( W^T \) is the weight data set of decoding process from the hidden layer to the output layer. P is the bias vector of the hidden layer and Q is the bias vector of the output layer. The data training process of the automatic encoder can be regarded as the process of finding the optimal parameters (weight ratio and bias value), so that the output can reconstruct the input as much as possible. Loss function minimization method is usually used to judge the degree of reconstruction, and the optimal solution is determined by analyzing the loss of information entropy between input and output data. On the premise of reaching reconstructed input, the hidden layer can be regarded as a low-dimensional feature extracted from the input data set after dimensionality reduction.\(^{[4]}\)

The method of stacked encoder requires only a small amount of sample data for machine training. And with appropriate classification and recognition technology, feature extraction and fault classification can be realized. It is more suitable for the situation where the current data volume of Automatic Verification pipeline is small. Therefore, this paper introduces SAE algorithm technology to realize the fault early warning model of automatic pipeline, fully demonstrating its powerful feature extraction ability and robustness of the method.\(^{[5]}\)

3. Fault Early Warning Model of Automatic Pipeline

The scale of automation pipeline of power grid verification system is expanding and its structure is becoming more and more complex. Much automation equipment causes complex operation of the whole system. Subtle abnormalities in different components can trigger a chain of failures. This brings considerable difficulties to the traditional shallow fault detection and diagnosis model. Therefore, this paper constructs an automatic pipeline fault early warning method based on deep learning algorithm. By means of data preprocessing and stacking of multi-layer automatic encoder AE, machine learning is carried out on the basis of the existing system operation data set, and a fault warning model for automatic pipeline of power verification system is obtained. The model architecture is shown in the following figure.

![Figure 2: Figure of the SAE model](image)

When applied to the verification system, the data training of the model is divided into two steps of pre-training and fine-tuning. Pre-training mainly selects unlabeled sample to input into the network, and completes the initial training of some automatic coders parameters by BP algorithm. Fine-tuning is to optimize and fine-tune the parameters of the whole network model through label samples, which makes the network verification more accurate.
4. Fault Early Warning Method Based on Deep Learning

4.1. Sample Data Set Selection
In order to ensure the precision and accuracy of the algorithm model for fault early warning, this paper uses the operation data of automatic pipeline equipment collected by Hainan Power Grid Co., Ltd. verification base as sample set to carry out model training and validation. In order to ensure the comprehensiveness of the sample data set and a sufficient number of samples, Operational monitoring data of all data acquisition equipment during normal operation and for a period of time before and after the failure are selected as the sample basis, and a specific number of samples are randomly selected as the unlabeled pre-training samples. For the label samples needed in the fine-tuning stage, the fault data provided by the same model manufacturer are collected as the labeled sample data.

4.2. Data Preprocessing
According to the characteristics of the actual collected sample data, combined with SAE deep learning method, it has strong ability to extract sample features. Five types of fault early warning are designed and seven kinds of feature sample data are selected, as shown in the table below.

Table 2: Fault early warning type and Sample data

| Fault early warning type                  | Sample data                                      |
|-----------------------------------------|-------------------------------------------------|
| Electromagnetic interference abnormal warning | - Electromagnetic field intensity               |
|                                         | - Track running speed                            |
|                                         | - Measuring current value, voltage value and phase angle |
| Blocked meter warning                   | - Reclosing instantaneous pulse interference value |
| Motor performance degradation warning   | - Conveyor belt deflection angle                |
| Verification of line body deformation warning | - The temperature monitoring value of verification unit’s key position |
| Verification unit abnormal warning      | - The monitoring data of motor component         |

In order to reduce the interval difference between data and calculation error, a standardized formula is adopted: $x_{new} = \frac{x - x_{mean}}{x_{std}}$. This formula performs data preprocessing on the collected data set. Where $x$ is the original value of the training set, $x_{mean}$ is the data mean of the training set, $x_{std}$ is the data standard deviation of the training set.

4.3. Fault early warning model
The structure of fault early warning model for verification pipeline is based on deep learning presented in this paper, which is shown in the following figure.
The input of the model is the seven kinds of operation parameters standardized before of the verification systems. The output of the model is the operation status of the verification system and the probability of five kinds of faults. The fault state whose probability value is higher than the preset threshold is the result of fault early warning. The steps of realizing the fault early warning model include:

S1: Seven classical parameters are selected from the collected verification center running data and equipment data of third-party manufacturers to form the original data set.

S2: Preprocessing the selected data, including standardization, de-rigidization and forward transformation. If the audio and video data are involved, the process of qualitative to quantitative transformation is needed.

S3: Select the classified label/unlabeled data from the standardized data to form the pre-training sample data set, select a different number of sample sets to train the model, and then analyze the learning ability and stability of the model.

S4: Unlabeled sample data in the pre-training sample set is used to pre-train the fault early warning model through BP algorithm.

S5: The labeled sample data in the pre-training sample set is used to optimize and fine-tune the model by BP algorithm.

S6: Save the algorithm model after training, select the test sample data with clear fault type to test the model after training. When the accuracy of fault early warning reaches more than 90%, it is considered that the algorithm model is really available.

4.4. Model Test

In order to ensure the sensitivity and accuracy of the algorithm model for fault early warning, this paper uses the operation log data collected from the verification base of Hainan Power Grid Co., Ltd. to test and verify. The purpose of this paper is to find out the relationship between the performance of the model and the number of AE layers and the number of samples in the pre-training set. Therefore, the performance of the model with AE layers of 1-5 layers is separately tested, and 1000 time points of normal operation and failure are selected as the training sample set, from which 250, 500, 750 and all data are randomly selected to form four groups of training sample sets to train the algorithm. In addition, 200 known fault/normal test samples are randomly selected to verify the performance of the model and test the accuracy of fault early warning. The experimental test is conducted based on the actual data, and the results are shown as follows. The results show that with the increase of model size and the number of pre-training samples, the accuracy of model fault prediction is also improved, and it has a better fault early warning performance for actual system operation data. The accuracy can reach more than 90%, which can be applied to the overall fault early warning system of verification center.
5. Epilogue

This paper presents a fault early warning method for power metering automation pipeline based on stacked automatic encoder deep learning algorithm. By comprehensively collecting the historical operation data of verification pipeline and the characteristic data provided by third-party manufacturers, a deep learning data sample is formed. Combed with SAE algorithm, a fault early warning model is designed, and the pre-training and optimization fine tuning of the algorithm model are realized by BP method. Finally, the performance of the model is tested by definite test data samples. The results show that the designed fault early warning model can ensure excellent accuracy and stability on the basis of ensuring the size of the model and the number of training samples, and can be used for daily fault early warning of verification system. The proposal of fault early warning method is of great significance to the target electric power metering automation pipeline. The realization and application of fault early warning model ensure that the automation pipeline can carry out real-time and comprehensive fault intelligent early warning and investigation, which makes the staff more intuitive in real-time fault monitoring of the automation pipeline, and also facilitates a more comprehensive understanding of the daily operation status of the automation pipeline.

Although deep learning technology has a good performance in intelligent fault early warning, the technical methods of neural network and machine learning are still in the exploratory stage, and need to be further studied and combined with practical application requirements. For the actual application of power automation pipeline, there are also the following aspects to be optimized and improved.

1) Fault early warning model realizes real-time fault early warning by collecting and analyzing real-time data, so whether the collected data is comprehensive and effective becomes the precondition of whether the output result of fault early warning is effective or not. This paper chooses 7 kinds of actual collected data as the sample basis, and suggests that the data acquisition unit of pipeline can be perfected and optimized, and the type and quantity of collected data can be enriched to ensure the sound of the diagnostic model.

2) As the technology of neural network and machine learning is still in the developing stage, there are still many research directions and possibilities that need to be further refined. For example, the optimal hidden layer nodes and its number, the initial value of parameter matrix and the selection of input data sample system are all topics that need to be discussed in deep learning. The goal is to make the effect of deep learning network the best.
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