Research on fault analysis of pumping station units based on stack auto-encoder

Linzhang Zhao1,3 and Chenghao Gao2

1 Taizhou River diversion Management Office in Jiangsu Province, Taixing 225321, Jiangsu
2 College of Water Conservancy and Hydropower, Hohai University, Nanjing 211100, Jiangsu
3 E-mail: 630769037@qq.com

Abstract. The stack Auto-encoder is applied to the fault analysis of pumping station units, and a fault analysis model based on stack automatic encoder is constructed. The model consists of an input layer, 3 hidden layers and an output layer to realize feature extraction and dimension reduction of the monitoring data of the pumping station unit. The network uses unsupervised layer-by-layer greedy methods to train, then uses backpropagation algorithms to optimize network parameters and uses the softmax classifier for classification. The experiment proves that the average classification accuracy rate of unit failure and different working conditions reaches 79.88% - 90%, which can provide a certain reference for unit failure analysis.

1. Introduction

For a long time, the maintenance of pumping station units in our country is based on prevention, adopting the plan maintenance mode and carrying out maintenance regularly. There are individual difference in service life between the components of the pumping station units. Even the same component has a certain difference in service life due to different operating environments and external influences [1-2]. Therefore, according to a fixed maintenance cycle for the planned maintenance of hydropower units, some parts have exceeded their service life but can not be repaired in time, so they can only be repaired and repaired after the sudden failure or accident of the unit, This will harm the stable operation of the unit and make the maintenance work in a hurry to cope with the situation; However, some parts are repaired in advance before they reach their service life, which not only reduces the availability of pumping station units, but also wastes manpower, material and financial resources. In addition, the unbroken units (or their main components) may not be up to the original level after maintenance [3]. It can be seen that there are many disadvantages in the traditional planned maintenance of pumping station units in our country, and condition maintenance is a feasible way to improve the equipment management and the modernization of maintenance technology.

With the development of computer science and technology, some fault diagnosis methods based on data analysis have appeared in recent years. According to the real-time state monitoring data of the pumping station units, the current health status of the unit is predicted and the faults are analyzed by means of data analysis. For example, Yan Guofei described a fault diagnosis method based on BP neural network in "Research and Development of Remote Condition Monitoring and Fault Diagnosis System for Pump Sets Conditions of Pumping Station"[4]. In this paper, 4 fault states and a normal state are selected, and the simulation data are collected through the simulation system. The fault
diagnosis model based on BP neural network is constructed and the fault classification is completed. Zhang Fei put forward an improved method of fault detection system based on BP neural network in the article "Application of improved BP Neural Network in Fault detection of Mine Ventilation System"[5]. Most of the models constructed by these methods are based on a few characteristic parameters to sample or filter the original data and then analyze the data samples. However, due to the complexity and uncertainty between features and faults, the accuracy of fault diagnosis is not high, and the ability of model analysis needs to be improved.

In order to solve the problem of fault diagnosis of pumping station unit, the data analysis model is constructed by using depth learning theory, and the fault analysis method of pump station units based on stack self-encoder is proposed in this paper. Depth learning refers to the ability to approach complex functions by learning a kind of deep nonlinear network structure, to input data distributed representation, and to show the powerful ability to learn the essential features of data sets from a few sample sets [6]. The stack auto-encoder is a mature network model in deep learning theory and has a good ability to learn the characteristics of data sets [7]. The stack self-encoder network model is used to learn the massive classification characteristics of the monitoring data of the pumping station unit, and the deep relationship between the data is fully explored, and the effective features that are favorable for classification are obtained for fault classification. Finally, the effectiveness of this method is proved by comparing with KNN, BP neural network and softmax regression model classification method.

2. Method and theory

2.1. Auto-encoder

Auto-encoder network generally consist of an input layer, a hidden layer, and an output layer. Suppose there is a set of unlabeled training samples \( x = \{x_1, x_2, ..., x_n \} \), the output is \( x' = \{x'_1, x'_2, ..., x'_n \} \), the optimization goal of the automatic encoder network is to obtain the output that is the most approximate input. Through the problem solving, the optimal expression of the input can be constructed, that is, the feature extraction is completed. The input \( x \) to the input layer becomes the activation value \( y \), which has the following relationship:

\[
y = f_\theta(x) = s(Wx + b)
\]  

(1)

In the upper expression \( s \) is a nonlinear function, such as a sigmoid function; \( \theta = \{W, b\} \) is a parameter set.

For the activation value \( y \) inverse reconstruction value \( z \), the following relationship exists:

\[
z = f_{\theta'}(y) = s(W'y + b')
\]  

(2)

In the upper expression, \( \theta' = \{W', b'\} \) is a parameter set, and the parameters in the two collections are limited to \( W' = W^\top \).

Adjust \( \theta \) and \( \theta' \), and minimize the reconstruction error \( L \), defined \( L \) as:

\[
L = \frac{1}{2} \|z - x\|^2
\]  

(3)

By solving the optimization problem, it can be considered that the best expression of the original input of the reconstruction error is obtained.

2.2. Sparse auto-encoder

If the information of the original input data is retained by the auto-encoder, it is not enough for the auto-encoder to learn an abstract representation of the essence. Therefore, it is necessary to add a certain constraint to the automatic encoder to learn a more complex nonlinear function and obtain a better feature representation [8]. The sparse coding algorithm is an unsupervised learning method used to find a set of "over-complete" basis vectors to represent sample data more efficiently. The purpose of
the sparse coding algorithm is to find a set of basis vectors \( \phi_i \), it can represent the input vector \( X \) as a linear combination of these base vectors:

\[
X = \sum_{i=1}^{k} a_i \phi_i \tag{4}
\]

Among them, the sparsity requirement for the coefficient \( a_i \) is: for a set of input vectors, make as few factors as possible that are much larger than zero. Thus the input data may be represented by a small number of components, to achieve a more abstract representation of the essential features of the input data. Then for a sparse autoencoder of \( m \) input vectors, the cost function is defined as:

\[
\min_{a_i, \phi} \sum_{i=1}^{m} \| x^{(j)} - \sum_{i=1}^{k} a_i \phi_i \|^2 + \lambda \sum_{i=1}^{k} S(a_i^{(j)}) \tag{5}
\]

Among them, \( S(a_i^{(j)}) \) is a sparse cost function function that penalizes sparseness far greater than zero to achieve a certain demanding sparse representation. \( \lambda \) is a variable that controls the degree of sparse cost function. By solving the optimal solution of the cost equation, a good reconstruction of the input satisfies certain sparsity requirements is achieved [9].

3. Algorithm design

3.1. Network structure

According to the characteristics of unit fault in pump station, the fault analysis model of unit adopts stack auto-encoder neural network. Stack self-encoder is a multilevel depth learning network based on sparse auto-encoder and taking each sparse auto-encoder as a layer. The data feature is extracted by stack auto-encoder and then classified by softmax regression model. Fault analysis model setup based on stack auto-encoder, including input layer, 3 hidden layers, and softmax classification layer. Figure 1 shows the basic model of the fault analysis system.

![Figure 1. Basic model diagram of fault analysis.](image)

The layered model of the pumping station unit failure analysis model is actually a sparse auto-encoder network corresponding to the layer model that constitutes the stack auto-encoder. The input data comes from the output data of the sparse auto-encoder completed by the previous layer. After learning this layer, the reconstructed data with lower dimension is obtained and used as the input of the next sparse auto-encoder model. Figure 2 shows the failure analysis model.

![Figure 2. Fault Analysis Model.](image)
3.2. Training method
Although the deep network has strong expressive ability and learning ability, it is prone to local optimal problems and gradient dispersion problems during the training process. The layer-by-layer greedy training method is a network training method proposed by Hinton based on deep belief network, which is a successful algorithm for deep network training [10]. The main idea of the algorithm is to train only one layer in the network at a time, we first train a network with only one hidden layer, and only start training a network with two hidden layers after the network training ends, and so on. Initialize the weight of the final depth network with the weights obtained by training each layer separately, then "fine adjustment" the entire network to optimize the training errors on the tagged training set by putting all the layers together [11-13].

Adequate network training requires a large amount of data, while untagged data is easily available. Compared with random initialization, after training the network with untagged data, the initial weights of each layer will be located in a better position in the parameter space, from which we can further fine-tune the weights [14-15]. The untagged data provide a lot of prior information about the patterns contained in the input data, so starting from these positions, starting the gradient descent can better converge to the local extremum and obtain a better classification model.

The whole process of unsupervised learning is as follows: the training of diagnosis system is first aimed at sparse self-encoder. After full training, the parameters are saved to the current layer, and the output of the current layer is taken as the input of the next layer. Start the training of the next layer sparse self-encoder until the penultimate layer [16-17]. The last layer uses softmax to classify features and use sample tags for supervised learning. The training steps are as follows:

1. The training data set is taken as the input of the input layer and the first layer automatic encoder is completely trained to obtain the network parameters and then calculate and output the first hidden layer.
2. Take the output of step 1 as the input of the second layer, train the second layer automatic encoder completely, get the parameters of the second layer network, calculate and output the third hidden layer.
3. Take the output of step 2 as the input of the third layer, fully train the third layer automatic encoder, get the parameters of the third layer network, calculate and output the third hidden layer.
4. The output of step 3 is used as the input of the softmax classifier, and then the network parameters of the softmax classifier are trained by using the original data mark.
5. Calculate the cost function of the entire network, and the partial derivative function value of each parameter of the entire network.
6. The network parameters of steps 1, 2 and 3 are used as the initialized values of the whole depth network parameters, and then the parameters near the minimum value of the upper cost function are iterated out by using the LBFS algorithm, which is the final optimal parameter of the whole network.

4. Experiment and result analysis

4.1. Experiment setup
Based on Matlab platform, the data collected from the pumping station of Taizhou River Management Office, Jiangsu Province. Most of the collected data is used for model training, and the rest of the data is used for model testing. The monitoring data includes the data of pumping station unit in normal operation and a small amount of data in case of failure. The training data set and the test data set both contain a certain number of normal operating data and fault data.

By pretreatment the monitoring data, the sample data of the hydro power unit is finally represented by 76 key features, including hydrology information, voltage and current information, hydro power unit detection information, and river channel detection information [18-19]. According to the actual operating experience of the existing pumping station unit, the data items irrelevant to the monitoring of the operation status of the pumping station unit are eliminated, and the data items related to the monitoring of the operating status of the 14 pumping station units are retained, including motor thrust.
bearing horizontal and vertical vibration, upper and lower horizontal and vertical vibration, X, Y direction shaft swing, Impeller shell X, Y direction swing, water guide bearing X, Y direction vibration, speed, flow, temperature, oil level and other data items [20-21].

Taking into account the current computing power and computational efficiency, the data is processed in batches for training and testing. In a batch of test data, the fault data mainly includes five types of typical faults: oil film whirl, rotor misalignment, rotor imbalance, static and dynamic friction and oil film oscillation. The number of samples for training and testing is shown in Table 1.

|                | normal | Oil film whirl | rotor misalignment | rotor imbalance | static and dynamic friction | oil film oscillation |
|----------------|--------|----------------|--------------------|-----------------|----------------------------|----------------------|
| The amount of training | 1198   | 158            | 162                | 162             | 166                        | 154                  |
| The amount of testing    | 302    | 38             | 36                 | 46              | 42                         | 36                   |
| Total amount            | 1200   | 196            | 198                | 208             | 208                        | 190                  |

4.2. Analysis of results

In order to further analyze the experimental data, the three shallow classifiers, RBM KNN, depth belief network DBN, are compared with this method under the same test data condition by using the model testing method and the partial depth learning method. The classification effect of each classification model is shown in Table 2.

| Model          | Accuracy rate |
|----------------|---------------|
| RBM+KNN        | 79%           |
| DBN            | 86%           |
| The method     | 90%           |

It can be seen from Table 2 that when classified by shallow model, the accuracy of RBM+KNN is 79%, DBN is 86%, and the method is 90%. It is found that the accuracy of this method is better than that of other methods, and the test time is faster than other methods. This is because the sparse automatic encoder can extract the features of the data quickly and accurately when the data latitude is small, and the nearest neighbor classification method can keep the features of the data according to the extracted features. According to the feature clustering method and the nearest K classes, more categories corresponding to the test data are selected.

In a batch of data of this research method, the training data set size is 2000×14. Since the training data set is small, the online training method can be used. Compared with the different iteration times, the nearest neighbor classifier is used to obtain the classification results, and 5 independent model tests are performed respectively. The model test results are shown in Table 3.

| Serial number | Number of iterations | Accuracy rate |
|---------------|----------------------|---------------|
| 1             | 10                   | 68%           |
| 2             | 50                   | 72%           |
| 3             | 80                   | 81%           |
| 4             | 110                  | 88%           |
| 5             | 135                  | 90%           |

As can be seen from Table 3 that the number of iterations is between 10 and 135, and the overall effect is better. The diagnostic system is used to check the operation failure of the pumping station unit, and the accuracy rate is reach up to 90%. Compared with the other two shallow models, the model
constructed by this study has better classification effect. This diagnostic system has higher reliability for fault analysis of the pumping station unit and provides a great help for the final diagnosis of the fault.

5. Conclusions and Outlook

According to the fault data characteristics of the pumping station unit, the fault analysis model of the pumping station unit is constructed by using the stack sparse auto-encoder network, and the monitoring data of the pumping station unit was tested.

The experimental results show that this method has more advantages in feature learning than other shallow neural network methods such as BP neural network. The fault analysis model of pump station unit has reference value for unit health condition and fault diagnosis.

This method can realize the feature adaptive extraction from the data itself to the classification results, and reduce the technical requirements for the signal processing of power station staff. With the increase of the number of iterations and the optimization of the network topology, the recognition accuracy will be obviously better than that of other existing classification methods. Further research can be carried out on the unlabeled monitoring data of power station, and a new diagnosis method from data end to fault type end of unit fault diagnosis can be explored.

References

[1] Zhou M H 2011 Research and Development of Remote Supervision and Analysis Platform of Main Machine Set Condition in Pumping Plant Yangzhou University
[2] N Srivastava, G E Hinton, A Krizhevsky, I Sutskever and R Salakhutdinov 2014 Journal of Machine Learning Research 15(1) pp 1929-1958
[3] Peng Z G, Zhang H and Li H 2008 East China Electric Power pp 127-130
[4] Yan G F 2012 Research and Development of Remote Condition Monitoring and Fault Diagnosis System for Pump Sets Conditions of Pumping Station Yangzhou University
[5] Zhang F, He Y Q and Zhang K 2013 Industry and Mine Automation pp 61-63
[6] Yin B C, Wang W T and Wang L C 2015 Review of Deep Learning Journal of Beijing University of Technology pp 48-59
[7] Deng J F and Zhang X L 2016 Journal of Computer Applications pp 697-702
[8] Lin S F, Sheng H X and Li Q W 2015 Microprocessors pp 47-51
[9] Dai X A, Guo S H, Ren Y, Yang X X and Liu H H 2016 Journal of University of Electronic Science and Technology of China pp 382-386
[10] Hinton G E, Osindero S and Teh Y W 2006 Neural computation p 54
[11] Wang K and Liu D M 2015 Journal of Chongqing University of Technology (Natural Science) pp 120-126
[12] Yang Shuai and Wang Peng 2018 Journal of Computer Applications 38(7) pp 1866-1871
[13] Xie Xianghui, Shan Deshan, Zhou Xiaohang 2018 Railway Engineering 5
[14] Liu H 2015 SAR Image Classification Based on Deep Feature Learning and Sparse Representation Xidian University
[15] Lu Y P 2016 Research on Deep Networks-Oriented Auto-Encoders Soochow University
[16] Xia L 2016 Optimizing Deep Learning Algorithm Based on Noisy Autoencoder Wuhan University of Science and Technology
[17] Luo Y X 2014 Experimental Study of Speed Up Techniques for Sparse Autoencoder Lanzhou University
[18] Dai Xiaoyi, Guo Shouheng, et al. 2016 Journal of University of Electronic Science and Technology of China 45(3) pp 382-386
[19] Cui Jiang, Tang Junxiang, Gong Chunying and Zhang Zhuoran 2017 Proceedings of the CSEE 37(19) pp 5696-5706
[20] Li Guoping 2017 Water Purification Technology 36(6) pp 100-106
[21] Zhang Guanxiang, et al. 2018 Mechanical & Electrical Technique of Hydropower Station 8