Auto-encoder based fault early warning model for primary fan of power plant

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Abstract: Primary fan system plays an important role in the operation of a power plant. However, due to the complicated working conditions of the primary fan and the strong coupling characteristics of multi-state variables, it is necessary to carry out feature engineering before using multivariate state estimation technique (MSET). In addition, no-linear operator should be designed to make sure matrix being invertible. This paper proposes an Auto-encoder based model to automatically construct a normal state memory matrix through unsupervised learning of neural networks. It reduces human intervention as well as the difficulty in giving a suitable non-linear operator design. This model is applied to the early warning of primary fan failure in a power plant in eastern Shandong Province.

1. Introduction
At present, due to the complexity of the power plant system, primary fan fault early warning is mainly implemented by data-driven methods [1], including multivariate statistical methods, neural network methods, support vector machines, etc. [2] Among them, MSET [3] was proposed by Singer in 1995 and has been successfully applied in nuclear power sensor calibration. This method has many advantages such as non-parameter setting, fast calculation speed and convenient deployment. However, the linear correlation between the vectors in the memory matrix will lead to difficulty to obtain the optimal solution. Therefore, principal component analysis (PCA) is needed to eliminate the linear relationship, and nonlinear operators are designed to ensure the reversibility of the matrix [1,4]. However, PCA cannot identify the nonlinear relationship between variables [2] and the nonlinear operators preserving the properties proposed by Singer [3] are hard to design.

The primary fan fault early warning model based on Auto-encoder (AE) proposed in this paper can realize unsupervised self-learning of primary fan monitoring points and find out the nonlinear relationship among features. Meanwhile through learning of normal operation data, the trained Auto-encoder can be regarded as an optimized memory matrix in MSET. After the new observation is input to the trained AE, the average Euclidian Distance [5] between the output result and the original data is taken as the prediction residual, and the average value and standard deviation (Std.) of the residual term in the rolling window period is calculated [6], so that the state of the new observation can be judged, and the abnormal data can be warned in time.
2. **Auto-encoder**

In 2006, Hinton proposed an unsupervised learning network called "Automatic Encoder" [7] to implement feature compression on high-dimensional data. At present, this framework has been widely used in speech recognition, image recognition, and has achieved remarkable results [8–12].

The basic AE is mainly a three-layer neural network structure consisting of an input layer, an intermediate layer and an output layer, in which the input layer and the output layer have the same dimension. AE training includes two processes: encoding and decoding. The encoding process converts the high-dimensional features of the input data into the low-dimensional features of the intermediate layer. The decoding process reconstructs the converted low-dimensional features and outputs data with the same input dimension, as shown in the following figure.

![Auto-encoder model](image)

Figure 1. Auto-encoder model

In the above model: \( n \) is the characteristic dimension of the input data; \( h_j \) \( j \in 1, ..., m \) is the neuron of the middle layer and is the estimated value of the output and \( m < n \); \( \hat{x}_i \) \( i \in 1, ..., n \) is the estimator of the output. In the encoding process, AE firstly performs linear weighting calculation on the vector \( x \), the weight \( W \) and the intercept \( b \), and then obtains the calculation the intermediate layer through activation function \( f(x) \).

\[
\hat{h} = f(Wx + b)
\]

(1)

In the decoding process, the intermediate layer does the same linear operation and then reconstructed estimated value \( \hat{x}_i \). The calculation process is as follows:

\[
\hat{x} = f'(W'x + b')
\]

(2)

Where \( W' \) and \( b' \) are the weight coefficients and intercepts of the output layer.

As an unsupervised learning, the input value and label set take the same data set. The training goal is to minimize the reconstruction error between data \( x \) and \( \hat{x} \). The expression of the loss function is:

\[
J_\theta = \frac{1}{M} \sum_{j=1}^{M} L(x, f'_\theta) + \alpha \sum (\theta^2)
\]

(3)

Note that: \( \alpha \sum (\theta^2) \) is a regularization term, which is used to prevent over-fitting of the model. \( \theta \) represents the weight \( W_{ij}^l \) between the two adjacent neurons in layer \( l \).

3. **AE-based primary fan fault early warning model**

3.1 **Data Preprocessing**

In order to prevent neurons from saturation, input data needs to be standardized. In addition, it will prevent the objective function from being affected by excessive deviation of a certain dimension in the learning process. The formula of normalized data here is:

\[
x_{\text{scaled}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

(4)
3.2 Model Construction

In this paper, 10 monitor points showing primary fan performances are selected as the basis for judging the primary fan operation state, such as outlet pressure, phase A current and so on, Table 1, to form the input data set $x_{i10}$, where $i$ represents time, 10 indicates the number of feature dimensions.

| No. | Indicators                          |
|-----|------------------------------------|
| 1   | primary fan outlet pressure         |
| 2   | primary fan A phase current         |
| 3   | primary fan front bearing vibration |
| 4   | primary bearing rear bearing vibration |
| 5   | primary fan outlet air volume       |
| 6   | primary fan motor lubricating oil pressure |
| 7   | primary fan front bearing temperature 1 |
| 8   | primary fan front bearing temperature 2 |
| 9   | primary fan rear bearing temperature 1 |
| 10  | primary fan rear bearing temperature 2 |

Table 1. Indicators affecting primary fan of power plant

The process of early warning process is as follows: firstly, using expert judgment method, the data of normal operation of the fan is selected and divided into training, validation and test set. Secondly, standardize the data to the (0 1) interval. Thirdly, construct the AE neural network. For the input and output layers, Sigmoid function is selected as the activation function, and Tanh function for the activation function of intermediate layers. Fourthly, gradient descent optimization calculation is carried out by using the adaptive moment estimation optimization algorithm (ADAM). The form of the objective function is expressed as:

$$
Loss = \frac{1}{M} \sum_{j=1}^{M} \| \hat{x} - x \|^2 + \frac{\lambda}{2(K + L)} \sum_{i=1}^{K} \sum_{j=1}^{L} W_{ij}^2
$$

Where, $\| \hat{x} - x \|^2$ means the Euclidean Distance between $\hat{x}$ and $x$; $\frac{\lambda}{2K} \sum_{i=1}^{K} \sum_{j=1}^{L} W_{ij}^2$ is the regularization term of the loss function; $K$ represents the number of layers of the network, and $L$ represents the number of neurons in each layer.

Therefore, the training process of AE is equivalent to the nonlinear feature dimension compression of the process memory matrix under MSET. At the same time, due to that the new input data can be directly brought into the model thereby calculating the residual error, it avoids the difficulty of designing a non-unique optimal solution in avoid of the irreversibility during matrix multiply [3].

3.3 Threshold Calculation Model

Since the trained AE learned the operating state of the primary fan under normal working conditions, the residual error between the model output and input should be very small when the new observation value comes from the normal working state. However, when it comes from the abnormal working conditions, the residual error will become larger. Especially in the early stage of equipment failure, the residual error of such abnormality should have a tendency to increase cumulatively. Here, we have chosen the mean value $E$ and standard deviation $S$ of the residual error in a given window as the indicators to measure the abnormal state of the equipment:

$$
r_k = \| \bar{x}_k - x_k \|$$

$$
E_i = \frac{1}{T} \sum_{k=1}^{T} r_k^i
$$

Where: $x_{max}$ and $x_{min}$ represent the maximum and minimum values of data $x$ in each dimension.
\[ S_i = \sqrt{\frac{1}{l-1} \sum_{k=1}^{l} (r_k^i - E_i)^2} \]  

(8)

Where: \( i \) represents the \( i \)-th window period, and \( l \) is the window size.

Residual error is calculated for test sets in normal data, and \( E_{i\text{Test}} \) and \( S_{i\text{Test}} \) are calculated in a rolling way, thus obtaining \( E_{\text{max Test}} = \text{Max}(E_{i\text{Test}}) \) and \( S_{\text{max Test}} = \text{Max}(S_{i\text{Test}}) \). At the same time, setting threshold coefficients \( \lambda_{\text{mean}} \) and \( \lambda_{\text{std}} \) can obtain the thresholds of \( E^* = \lambda_{\text{mean}} E_{\text{max Test}} \) and \( S^* = \lambda_{\text{std}} S_{\text{max Test}} \).

4. Data Experimental Results

The experimental data are taken from the PI database of a power generation company in eastern Shandong Province. The time range is from November 1 to 30, 2018. There are 156,000 valid data in total, with a time interval of 10 seconds, including 1,000 fault data. In the training process, 155,000 data were divided into training sets, verification sets and test sets according to the proportion of 50%, 30% and 20%. Among them, the test set is used to calculate the optimal thresholds \( E^* \) and \( S^* \). Note that the vector of residual error is normalized and compressed to the range of \([0, 1]\). Meanwhile, for the sake of simplicity, the calculated mean threshold is 0.66 and the standard deviation threshold is 0.6.

The calculation process of the whole model is shown in Figure 2.

Step 1: Select data of normal operating state of the primary fan
Step 2: Split the data into training, validating and test parts.
Step 3: Train the auto-encoder.
Step 4: Calculate the residual error of test data.
Step 5: Calculate mean/standard deviation (std) of the residual error using a rolling window and decide the mean/std threshold.
Step 6: Compare the threshold with the mean/std of a new observer and make a judgment.

Figure 2. Workflow of Auto-encoder based primary fan of power plant

Figure 3 and Figure 4 below show the warning effect of equipment failure. Figure 3 shows that 1413 data exceed \( E^* \). Fig. 4 shows that 709 data exceed \( S^* \). Through the analysis of the above results, we can see that (1) the threshold based on the mean value is used to judge the early warning of equipment failure earlier than the time when the equipment failure occurs, and its accuracy rate is 70.77%, but the recall rate reaches 100%. This shows that although there will be some misjudgment in the model, all the fault data have not been missed. (2) The threshold based on standard deviation makes little contribution to the judgment of equipment failure early warning, with the accuracy rate of 36.81% and the recall rate of only 26.1%. This shows that from the distribution of standard deviation of residual error, there is not much difference in standard deviation between normal data and abnormal data. (3) Average the normalized standard deviation of the residual error, using a window size of 100. As can be seen from Fig. 5, the mean value and the averaged the standard deviation shows the same trend. This means that, to some extent, the standard deviation of residual error reflects the abnormality of data. Therefore, further fault data sets are needed to improve a more accurate residual standard deviation threshold.
Figure 3. Mean of residual errors and threshold

Figure 4. Std. of residual errors and threshold

Figure 5. Mean-Std. of residual errors
5. Conclusion

The monitor points that affect the working conditions of primary fans in power plants are complex and diverse. Facing high-dimensional data, the traditional multiple state estimation (MSET) method needs to solve the problems of feature compression and matrix reversibility. In addition, as the amount of data increases, the calculation speed of the traditional algorithm will also decrease significantly.

The primary fan fault early warning model based on Auto-encoder proposed in this paper can learn the relations among fan monitoring points in an unsupervised way. This will automatically reduce dimensions of high-dimensional data, and find non-linear relationships between features. At the same time, the trained AE is used as the optimized MSET model, which avoids the difficulty of designing nonlinear operators. The model is applied in practice, and the residual mean threshold and residual standard deviation threshold are taken as the criteria to judge the running state of the equipment. In the future, further research and exploration will be carried out in increasing the depth of the model, introducing new network structure and designing threshold evaluation criteria.

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