Torque anomaly detection of nuclear power electric valve actuator based on DAE-WDSVVD

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Abstract—The abnormal detection of nuclear power electric valve actuator components can effectively improve its operation safety and reliability. With the rise of artificial intelligence technology, data-driven fault diagnosis methods have become more and more popular. However, in practical application, there are few or almost no fault data of valve actuator. For the problem of anomaly detection of actuator components of valve in the scenario of only normal data, an anomaly detection method based on the fusion of deep autoencoder (DAE) and weighted deep support vector data description (WDSVVD) is proposed. It uses normal data to train the depth self-encoder, and the reconstruction error of the depth self-encoder to train the support vector data description. Compared with the traditional anomaly detection method, it significantly improves the anomaly detection accuracy and can realize more sensitive and robust component anomaly detection.

1. Introduction
Since the fault of nuclear power plant has certain uncertainty, it is difficult to complete all diagnosis tasks only with the experience operators. Therefore, scholars have done lots of research on the fault diagnosis of nuclear power plant. Now, the generally recognized fault diagnosis methods are mainly divided into three categories: knowledge-based, data-driven and analytical methods.

- Knowledge-based method: There is no need to establish a mathematical model of the system, and the results are easily to understand [1]. However, it is difficult to acquire expert knowledge. There are matching conflicts and combination explosions in the reasoning process [2]. Representative algorithms are expert systems, multi-layer flow models, signed digraphs [3].

- Data-driven method: Accurate data-driven model is not required, the modeling process is relatively simple, the generality and applicability are well [4-5]. But, it is difficult to obtain sample learning data, sensitive to data changes, and difficult to be convinced with operators [6]. Representative Algorithm are artificial neural network, support vector machine [7].

- Analytical model: The physical meaning is clear and easily to interpret. There is no need to provide sample data [8]. However, the modeling process is complex and not have the ability of backward reasoning [9]. Representative Algorithm are qualitative mathematical model and analytical model.

Although knowledge-based, data-driven and model-driven fault diagnosis methods have achieved good results, the current research mainly focuses on the scenarios with sufficient fault data. In the actual operation of electric valve actuators in nuclear power plants, the fault data are often very few[10]. For
the new nuclear power electric valves put into operation, there are often only normal data but no fault data under the normal operation. At present, there are relatively few studies on fault detection of nuclear power electric valve actuator under the scenario of only normal data.

Deep autoencoder (DAE) and a weighted deep support vector data description (WDSVD) are proposed for fault detection of nuclear power electric valve actuator with only normal data. The DAE-WDSVDD fault detection method based on the fusion of WDSVDD improves the fault detection accuracy of the nuclear power electric valve actuator.

2. Experiment
The valve stem is the main stressed part, and it is impossible to directly measure its stress without damaging the valve itself. According to the thevenin's principle, Young's modulus and Poisson's ratio, the valve stem is in a regular cylindrical shape and the sensor is close to the load, the stress and strain are proportional to each other, as shown in Equation 1. The axial force can be calculated from the strain as long as the material properties and cross-sectional area are known. This project will detect the torque rod fault, stroke fault and opening torque fault of the electric valve actuator through the strain gage bridge circuit and laser displacement sensor.

\[
\delta = \frac{F}{S} \quad (1)
\]

\[
E = \frac{\delta}{\varepsilon} \quad (2)
\]

Combine with (1) and (2):

\[
\Delta F = S \cdot E \cdot \Delta \varepsilon \quad (3)
\]

where \( \delta \) is the stress, \( F \) is the friction force, \( E \) is the elastic modulus, \( \varepsilon \) is strain.

The relationship between the voltage change and the strain is:

\[
\Delta U_0 = \frac{\Delta U}{4} k (\varepsilon_1 - \varepsilon_2 + \varepsilon_3 - \varepsilon_4) \quad (4)
\]

Since four identical strain gauges are used, when two strain gauges are stretched, the other two strain gauges will be compressed with equal size and opposite direction. Then the above formula (4) can be simplified as:

\[
\Delta U_0 = \frac{\Delta U}{4} k \Delta \varepsilon \quad (5)
\]

\[
k = (1 + 2\mu) \quad (6)
\]

Where, \( K \) is the sensitivity coefficient of the strain gauge, \( \mu \) is the Poisson's ratio of the resistance strain gauge.

3. Depth Self-Coding Algorithm
Setting the input of the DAE \( X = (x_1, x_2, \cdots x_n) \in R^{m \times n} \), of which \( x_i \) \((i = 1, 2, \cdots n) \in R^{1 \times n}\), \( n \) is the number of samples, and \( m \) is the number of measuring points contained in various training sample, then the DAE first encodes the input \( X \) using the encoder shown in Eq.(7) to obtain an encoding matrix \( H \in R^{m \times n} \), Where \( V \) is the number of neurons contained in the last network layer of the encoder. The dimensionality of the input \( X \) is generally reduced with the encoder shown in Eq.(8). The DAE decodes \( H \) using the decoder shown in Eq.(8) to obtain a reconstruction matrix of the input
\( \hat{X} = (\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_n) \in R^{n_{\text{new}}} \), \( \hat{x} \ (i = 1, 2, \cdots, n) \in R^{1_{\text{new}}} \) is the number of samples, and \( m \) is the number of measuring points contained in various training sample. the DAE minimizes the sum of the input \( X \) and the reconstruction matrix described with Equ.9 to determine the encoder and decoder parameters.

\[
H = f_{\text{encoder}}(X) \quad (7)
\]

\[
\hat{X} = f_{\text{decoder}}(H) \quad (8)
\]

\[
J_{\text{DAE}} = \frac{1}{2} \sum_{i=1}^{n} \| x_i - \hat{x}_i \|_2^2 \quad (9)
\]

The input data can be compressed and reconstructed with DAE. A well-trained DAE can ensure the error between the input and the reconstructed matrix is small enough. If the DAE is trained with the normal samples of the nuclear power electric valve actuator, the error between any normal sample and the corresponding DAE reconstruction vector is small. The parameters between the encoder \( X_{\text{new}} \in R^{1_{\text{new}}} \) and decoder \( \hat{X}_{\text{new}} \in R^{1_{\text{new}}} \) are determined with the error between the input \( X \) and the reconstruction matrix \( \| x_{\text{new}} - \hat{x}_{\text{new}} \|_2 \).

4. Weighted depth support vector data description

Deep SVDD (weighted deep support vector data description, WDSVDD) is a new method developed on the basis of SVDD, whose basic idea is to extract features through deep learning network. And then an end-to-end anomaly detection network model is construct on that basis of the depth feature. Compare with that traditional SVDD method, The data feature representation is obtained by using multiple feature extraction layers instead of a simple single-layer kernel mapping.

For the training sample set \( \{ X_i \in R^m, i = 1, 2, \cdots, n \} \), the multi-layer feature extraction process can be described as a functional relationship

\[
\begin{align*}
  y_i^{(1)} &= \phi^{(1)}(x_i; W^{(1)}) \\
  y_i^{(2)} &= \phi^{(2)}(y_i^{(1)}; W^{(2)}) \\
  & \vdots \\
  y_i^{(L)} &= \phi^{(L)}(y_i^{(L-1)}; W^{(L)})
\end{align*}
\]

\( \phi^{(l)}(1 \leq l \leq L) \) representing the layer-by-layer nonlinear mapping function relation in the deep network, \( W(l) \ (1 \leq l \leq L) \) represents the layer \( L_{\text{th}} \) network weight parameter. The final extracted features are as follows:

\[
y_i^{(L)} = \Phi(x_i; W) = \Phi^{(L)}(\Phi^{(L-1)}(\cdots(\Phi^{(1)}(x_i; W^{(1)}))\cdots; W^{(L-1)}); W^{(L)})
\]

Among \( W = \{ W^{(1)}, W^{(2)}, \cdots, W^{(L)} \} \) represents the entire set of parameters of the deep web.

The optimization objective of the depth SVDD model is to distribute the output depth features as densely as possible in a hypersphere with radius \( R \) and center \( o \) with training, and the corresponding optimization objective function as the Equ.12.

\[
\min_{R, W} R^2 + \frac{1}{vn} \sum_{i=1}^{n} \max \left\{ 0, \| \Phi(x_i; W) - O \|^2 - R^2 \right\} + \frac{\lambda}{2} \sum_{l=1}^{L} \| W^{(l)} \|_F^2
\]

Where \( \nu \) is an equilibrium parameter to adjust the influence of abnormal data points in vitro, \( \lambda \) is a penalty coefficient for the size of the network weight, and \( o \) is the center of the sphere specified a priori. In a single classification task, it is generally assumed that the training data sets are all normal samples, and the objective function can be further simplified to

\[
\min_{W} \frac{1}{n} \sum_{i=1}^{n} \| \Phi(x_i; W) - O \|^2 + \frac{\lambda}{2} \sum_{l=1}^{L} \| W^{(l)} \|_F^2
\]
The weight parameter $W$ is optimized with the deep network optimization algorithm (such as Adam optimization algorithm), and the training samples can be gathered near the center $o$ of the hypersphere in the deep feature space. Thus, a hypersphere describing the normal training data is formed, and the network weight parameters obtained from the training are $W^*$. For the test sample, the monitoring index of the abnormality degree $y_i^T = \Phi(x_i; w^*)$ is defined as the depth feature of the point. The square of the distance to the center $o$ of the hypersphere, that is:

$$D_i = \|y_i^T - o\|^2 = \|\Phi(x_i; w^*) - o\|^2$$

(14)

5. Test Results and Discussions

The DAE-WDSVVD algorithm is used to carry out the research on anomaly detection of nuclear power electric valve actuator. Firstly, the normal samples of nuclear power electric valve actuator are used to train the depth self encoder, and the algorithm parameters are adjusted through the verification set. After the training, the test set of normal samples is input into the depth self encoder to compare the reconstruction errors of normal data and fault data. In this paper, the root mean square error shown in Equ.15 is used to measure the reconstruction error.

$$E_{RMSE} = \sqrt{\frac{1}{2n} \sum_{t=1}^{n} \|X^t - \hat{X}^t\|^2}$$

(15)

Where ERMSE is the root mean square error, $X$ is the original input data, $n$ is the number of samples, $X_i$ and $\hat{X}_i$ are the $i_{th}$ sample of the original input data and the reconstructed individual of the original data respectively.
The comparison of anomaly detection accuracy between dae-wdsvdd method and SVM proposed in this paper is shown in Tab.1. It can be seen from Tab.1 that the accuracy of dae-wdsvdd on the training set and test set data of normal data is significantly better than that of SVM method, which verifies the superiority of the method proposed in this paper.

6. Conclusion
In view of the anomaly detection problem of nuclear power electric valve actuator in the scenario of normal training samples, DAE-WDSVDD anomaly detection algorithm based on deep self encoder and deep support vector data description fusion is proposed. In this method, the data is compressed and reconstructed by depth self encoder, and the reconstruction error threshold is determined by weighted depth support vector data description. Compared with support vector meter, the proposed method can significantly improve the anomaly detection accuracy of nuclear power electric valve actuator, realize sensitive and robust anomaly detection of nuclear power electric valve actuator components, and improve the operation safety and reliability of nuclear power electric valve actuator.

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