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Research on intelligent fault diagnosis method for nuclear power plant based on correlation analysis and deep belief network

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ABSTRACT

The complexity and safety requirements for Nuclear power plants (NPP) warrant a reliable fault diagnosis approach. In this paper, we present a fault diagnosis method based on Correlation Analysis and Deep Belief Network. We utilized the feature selection capability of Correlation Analysis for dimensionality reduction and deep belief network for fault identification. We also discussed the implementation of the algorithm and the process of model building that is characteristics of NPP. To illustrate the performance of the proposed fault diagnosis model, we utilized Personal Computer Transient Analyzer (PCTRAN). In addition, we also compared the fault diagnostic results from back-propagation neural network and support vector machine with our method. The results show that the proposed method has obvious advantages over other methods, and would be of profound guiding significance to the fault diagnosis of NPP.

1. Introduction

The nuclear power plant is a complex, non-linear and highly dynamic system, composed of many devices, functional requirements. A failure of one device is likely to cause a cascade of failures, capable of adversely affecting the NPP's operation. In order to reduce the occurrence of components failure in NPP and to make timely feedback when faults occur, a reliable fault diagnosis approach is required. Increasingly, intelligent fault diagnosis approach is gradually attracting more attention because of the inherent saturation and drawbacks in the traditional methods.

Recently, a number of research progress have been made on the application of intelligent algorithms for fault diagnosis. Some machine learning and artificial intelligence approach such as the artificial neural network (ANN) (Mo et al., 2007), fuzzy-logic (Kang et al., 2017), expert system (Zhang et al., 1994; Smith et al., 1994), support vector machine (SVM) (Yi et al., 2015; Sun and Huang, 2011; Sun et al., 2016), etc., have been developed. In manuscript (Zhou et al., 2000), a new approach that combines genetic algorithms (GAs) and classical probability with an expert knowledge base is used to assess the state of NPP. The GA population undergoes a transformation that produces an individual adapted to the NPP's condition, and experiments show that this method has the comparative adaptability to diagnose false signals and dynamic faults, accommodate imperfect expert knowledge, and detect illusive signals and other phenomena. In manuscript (Da Costa et al., 2011), a neuro-fuzzy method is used to build a system for efficient transient identification. The proposed system uses artificial neural networks (ANN) as first level transient diagnostic. After preliminary transient type identification by ANN, a fuzzy logic inference machine analyzes the results and specifies the reliability. Nabeshima et al. (2002), proposed a hybrid monitoring system for nuclear reactor utilizing neural networks and a rule-based real-time expert system, where the neural network is used to successfully model the plant dynamics and detect anomalies earlier than the conventional alarm system and the real-time expert system satisfactorily display the system status by using the outputs of neural networks and a priori knowledge base.

As in typical complex, intricate, nonlinear dynamic system, NPP is embodied in numerous state-parameters, a large variety of faults and diversified fault features. In view of such complexity, traditional fault diagnostic method is limited for complex fault situations mainly because of its poor ability to learn feature from complex data. Deep learning (DL) and dimensionality reduction algorithms provide a new way to diagnose faults in complex systems.

One of the most effective methods for feature selection and dimensionality reduction is the feature filtering capability of correlation analysis (CA), which defines the correlation between individual features and each category labels, based on the specific relevance such as the classification ability of individual features (Yu and Liu, 2004). In this approach, the feature subset with high classification ability is selected according to the correlation. It can substantially eliminate weak correlation or even irrelevant features in the data for classification and achieve dimensionality reduction.

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Deep Learning is one of the recent advancements in ANN. It is a type of multi-layer network learning model capable of forming high-level abstract to represent attribute categories or features by combining low-level features and to discover the distributed feature representation of data, which makes it good at feature learning. Currently, DL has been successfully applied in many fields. Deng et al. (2013) describe the application of deep learning architecture for speech recognition. Krizhevsky et al. (2012) applied the convolution neural network (CNN) to LSVRC-2010 ImageNet training set recognition and produced optimal recognition performance. In manuscript (Silver et al., 2016), they successfully applied DL to the game of Go and developed the corresponding program AlphaGo, which defeated top players Shishi Li and Jie Ke respectively in 2015 and 2017. However, the application of DL in fault diagnosis is still at the primary stage. A novel multi-sensor health diagnosis method using deep belief network (DBN) is proposed by Tamilselvan and Wang (2013), and aircraft engine health diagnosis and electric power transformer health diagnosis are employed to demonstrate the efficacy of the proposed approach. In manuscript (Jia et al., 2016), a novel intelligent diagnosis method based on deep neural networks (DNN) is used for fault diagnosis of rotating machinery, which is validated using datasets from rolling element bearings and planetary gearboxes. Jing et al. (2017) presented a convolution neural network (CNN) based feature learning and fault diagnosis method for the condition monitoring of gearbox. In manuscript (Sun et al., 2016), a sparse auto-encoder-based deep neural network is investigated for induction motor fault diagnosis.

In this paper, we propose a new method based on CA and DBN for NPP fault diagnosis. CA is used to filter irrelevant or weak correlative parameters in fault data and retain useful parameters to reduce the dimension, which provides the basis for further reduction of data processing complexity and enhancement of training and operation speed of the model. DBN has multi-level feature extraction capabilities and its training process is divided into two phases: pre-training and fine-tuning. Among them, unsupervised training is employed in the pre-training phase and supervised training is used in the fine-tuning phase. This training method can extract the essential characteristics from fault data. Compared with traditional intelligent fault diagnosis method, the proposed method has higher fault recognition rate.

The rest of the paper is organized as follows: in section 2, relevant concept of CA and DBN is briefly introduced. In section 3, a new NPP fault diagnosis model based on DBN is proposed. Experiments and results are presented in section 4. Section 5 concludes the paper.

2. Fault diagnosis method

2.1. Dimensionality reduction based on CA

High-dimensional data contains a number of redundant information about the observed parameters. Dimensionality reduction is necessary to remove the noise in the data and to reduce computational time for the algorithm. In addition, reduced dimension aids generalization and classification ability, and reduces the training time of the classifier. The goal of dimensionality reduction is to find a low-dimensional representation which can effectively describe the characteristics in high-dimensional data to avoid dimensionality problems.

The data dimensionality reduction method can be divided into two types: feature selection and feature extraction. In feature selection, appropriate feature subset is selected from the original feature set according to certain rules to reflect the statistical correlation in the characteristic data. Feature extraction is to transform feature data from high-dimensional space to low-dimensional space according to certain rules so that the classification information scattered in the original feature will be concentrated to a small number of new features. In this paper, the Pearson correlation coefficient algorithm (Yu and Liu, 2004) is chosen to realize feature selection through dimensionality reduction, which has many advantages, such as high efficiency, accurate calculation, strong practicability, etc. The correlation coefficient r is used to measure the correlation between variable x and y, and the value range of r is [-1,1]; we define:

Table 1
The descriptions of the correlation coefficient.

Ranges	Descriptions
$0.8 < \|r\| \le 1$	Extremely correlated
$0.6 < \|r\| \le 0.8$	Strong correlation
$0.4 < \|r\| \le 0.6$	medium correlation
$0.2 < \|r\| \le 0.4$	weak correlation
$0 \le \|r\| \le 0.2$	hardly correlated

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{1}$$

where $\bar{x}$ and $\bar{y}$ represent the mean of data set x and y, respectively. When $r > 0$, it indicates that variable x and variable y are positively correlated, and when $r < 0$, variable x and variable y are negatively correlated. The larger $|r|$ is, the more significant relationship between x and y. Generally, the variable correlation degrees can be measured as in Table 1.

In this paper, the threshold λ is selected as the feature parameter selection criteria. When $|r| \ge \lambda$, the corresponding parameter will be selected as characteristic parameter. When $|r| < \lambda$, the parameter is considered to have little effect on fault classification task, and it can be discarded directly.

2.2. Deep learning

DL is a new branch of machine learning and a new development in the neural network. Its motivation is to establish an intelligent system that can mimic the human brain to analyze the data, through the combination of low-level features to form a more abstract high-level representation of the attributes or characteristics to find the representation of data feature distribution. Classified by the training mechanism, DL belongs to unsupervised learning.

In the pioneering work of Geoffrey Hinton (Hinton and Salakhutdinov, 2006), the differences between DL and traditional neural network are presented as follows: (i) traditional neural networks generally have only two or three-layer networks, it's parameters, computational units, ability to express complex functions, and learning ability are limited; however, DNN may have up to five or ten layers, or even more networks; (ii) In the aspect of feature learning, DNN is trained by layer-by-layer learning mechanism, which makes it easier to classify or forecast by changing the feature representation of samples in the original space to a new feature space. These features make DL a unique advantage in portraying data's intrinsic information and have rapidly developed in various fields in recent years.

2.2.1. Restricted Boltzmann Machine

Restricted Boltzmann Machine (RBM) is a two-layer neural network, having one layer of visible units and one layer of hidden units (Hinton et al., 1985). Furthermore, each visible unit is connected to all the hidden units, and this connection is undirected, so each hidden unit is also connected to all the visible units. The bias unit is connected to all the visible units and all the hidden units. To make learning easier, the network is restricted so that no visible unit is connected to any other visible unit and no hidden unit is connected to any other hidden unit (see Fig. 1).

As an energy-based model, RBM's energy function $E(\boldsymbol{v}, \boldsymbol{h})$ of joint configuration $(\boldsymbol{v}, \boldsymbol{h})$ between visible units and hidden units is:

$$E(\boldsymbol{v}, \boldsymbol{h}; \theta) = -\sum_i b_i v_i - \sum_j c_j h_j - \sum_{i,j} v_i h_j w_{ij} \tag{2}$$