Intelligent fault diagnosis for nuclear power plant based on deep belief network and support vector machine

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Abstract: For the fault diagnosis of nuclear power plant, using the deep learning and support vector machine technology, a novel intelligent diagnosis method was proposed, which combined the deep learning feature extraction and support vector machine pattern recognition. The characteristics of fault data was extracted adaptively with deep belief network, then support vector machine classification model was used for diagnosing the fault of nuclear power plant. The normal and fault data from Qinshan II nuclear power plant was normalized. The deep belief network was given unsupervised training with training samples consisted of normalized data. The output of deep belief network was used for training support vector machine classification model. The result indicates that the method can diagnose fault correctly and the accuracy can be above 90%.
Keyword: nuclear safety; fault diagnosis; deep belief network; support vector machine

1 Introduction

As a clean energy, nuclear energy has a good prospect for development. With the development of nuclear power, the importance of nuclear safety has been paid more attention. Nuclear power plant is a complex physical and thermal system with potential radioactive dangers. In order to make the nuclear power plant run safely and effectively, it is necessary to diagnose faults accurately as soon as possible, for avoiding malfunctions as much as possible or mitigating the consequences of malfunctions.

Deep belief network (DBN) has a strong ability to extract features from samples, which can process high-dimensional and nonlinear data. Through unsupervised training layer by layer, the distributed feature representation of data is found. As a method of feature extraction, DBN is good versatility and adaptability [1-3]. Support vector machine (SVM) was proposed according to statistical learning theory by Vapnik in 1995, which is a two-kind classifier based on structural risk minimization. It can effectively prevent over-fitting and local optimal problem. Besides, with the introduction of kernel functions, the curse of dimensionality was solved skillfully, SVM has advantages of classification for small samples [4-5]. Hence aiming at some of typical faults of nuclear power plant, DBN was used to extract features of samples, while SVM diagnoses faults to achieve intelligent fault diagnosis of nuclear power plant.

2 Theory

2.1 The deep belief network

Restricted Boltzmann Machine (RBM) is a kind of generating random neural network, which contains a hidden layer consisting of random hidden units and a visible layer composed of random visible units. Both visible nodes and hidden nodes are bivariate, their state is {0, 1}. RBM can be represented as a bipartite graph model, the neurons in the adjacent layer are all connected, while the neurons in the layer are not [6]. DBN consists of several stacked RBMs. Figure 1 shows a schematic of the DBN.

The bottom visible nodes receive input data. The number of neurons in the visible layer of each RBM is

Received date: November 15, 2018
(Revised date: January 10, 2019)

equal to the number of neurons in the hidden layer of the previous RBM, and the output of the hidden layer is the input of the next RBM visible layer. The training of DBN is generally divided into two processes: unsupervised training and supervised fine-tuning. In the process of unsupervised training, a greedy training algorithm is adopted to train RBMs one by one. Then the BP algorithm is used for fine- tuning. In order to extract features, we only conduct unsupervised training, so the output of the network is extracted feature data.

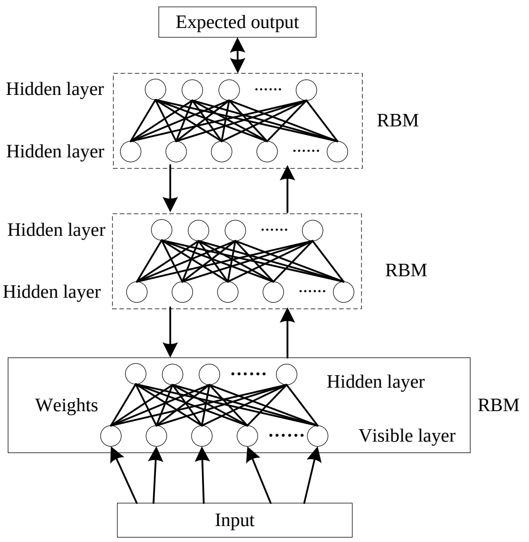

Fig.1 DBN design.

2.2 Support vector machine

SVM is a kind of machine learning method, whose basic model is the linear classifier with the largest geometric interval in feature space. The strategy of SVM is to maximize the geometric interval and can be represented as a convex quadratic programming problem, its basic algorithm is as follows:

For a linearly separable two-pattern classification problem, separating hyperplane can be expressed as follows:

$$g(X)=\langle \omega, X\rangle+b \tag{1}$$

For a given data set, such as:

$$T=\{(X_1,y_1),(X_2,y_2),\ldots,(X_N,y_N)\}$$

Where X_i is one of the sample data, y_i is the label of category.

For one data (X_i,y_i) in T and separating hyperplane (ω,b), its geometric interval is expressed as:

$$\delta=\frac{1}{\|\omega\|}|g(X)| \tag{2}$$

In order to maximize the geometric interval, the minimum value of $\|\omega\|$ is required. Therefore, two-pattern classification problems can be transformed into a constrained minimum value problem, such that:

$$\begin{gathered}\min \frac{1}{2}\|\omega\|^2 \\ s.t. y_i[(\omega\cdot X_i)+b]-1\geq 0(i=1,2,\ldots,N)\end{gathered} \tag{3}$$

In order to solve the convex quadratic programming problem, Lagrange multiplier α is introduced. Solving the minimum of ω is transformed to solving the minimum of α, which take the form:

$$\omega=\sum_{i=1}^{N}(\alpha_i y_i X_i) \tag{4}$$

$$g(X)=\sum_{i=1}^{N}\alpha_i y_i\langle X_i, X\rangle+b \tag{5}$$

To reduce the influence of noise, relaxation variable is introduced to the objective function, so the optimization is expressed as:

$$\begin{gathered}\min \frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{N}\xi_i \\ s.t. y_i[(\omega\cdot X_i)+b]\geq 1-\xi_i\end{gathered} \tag{6}$$

Where C is the penalty factor, which determines how seriously you take outliers. The greater C, the more attention paid to the outliers[7].

The approach to solve inseparable problems is to map the feature space of a sample to a high-dimensional linear space through kernel functions. There are some commonly used functions, such as polynomial kernel function, linear kernel function, radial basis function and sigmoid kernel function. The expression of radial basis function used in this paper is as follows:

$$K(x_i,x_j)=\exp\left(-\|x_i-x_j\|^d\right)/2\gamma^2 \tag{7}$$

Where d is function's order, γ is function's width.

3 Fault diagnosis with DBN and SVM

The normal operation and failure data of pressurized water reactor at the end of the core are obtained by using PCTRAN simulation software. DBN is trained according to the simulation data, and the output of the last layer DBN is adaptively extracted feature. DBN's output is SVM's input training. Figure 2 shows the structure of fault diagnosis.

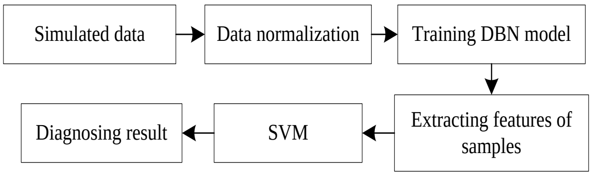

Fig.2 A structural representation of fault diagnosis.

3.1 Sample Processing

Loss of Coolant Accident (LOCA), Steam Generator Tube Rupture (SGTR), Main Steam Line Break (MSLB), Inadvertent Rod Withdrawn (IRW) and the normal state are chosen. Samples consist of data extracted in an equal interval at every time from normal operating data and four kinds of malfunctions data. The total number of training samples is 2000, of which each state is 400. The number of test samples is 300, of which each state is 60, like Table 1 showed. Both training and test samples' parameters are 62.

Table 1 Fives states of nuclear power plant

Operating states	Number of training samples	Number of test samples	Labels
Normal	400	60	1
LOCA	400	60	2
MSLB	400	60	3
SGTR	400	60	4
IRW	400	60	5

Before training DBN, the samples need to be normalized. The formula, which normalizes data to [0, 1] as follows:

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{8}$$

3.2 SVM model establishing

The parameter setting of DBN unsupervised training is shown in Table 2.

Table 2 Parameter setting of DBN

Structure of network	62-40-20-10
iterations	50
Learning rate	0.7
Momentum	0.5
Decay	0.01
Number of processing batch	20

Feature samples extracted from DBN are the input samples to train SVM classification model. Kernel function is chosen to be radial basis function, the kernel width gamma and penalty factor C are optimized by grid search method. The basic idea of grid search method is to set the range of penalty factor C and kernel function parameter gamma in advance, and to take a number every step. Two parameter values are tried and trained to get the models one by one. Finally, the best combination of parameters is chosen, which can make the highest classification accuracy of the model. In this paper, parameters C and gamma are set to [2-10,210], step length is 4.5. Figure 3 shows the searching result.

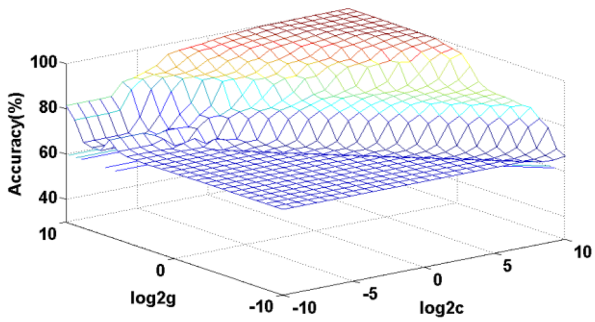

Fig.3 The result of grid search method.

In Fig.3, Z-axis coordinates are: the classification accuracy of training samples by SVM model determined by two parameters; X-axis coordinates are: logarithm of parameter C with bottom 2; Y-axis coordinates are: logarithm of parameter gamma with bottom 2. The higher the accuracy, the better the effect of model training. The combination of parameters with the highest accuracy is the most optimal parameters. The result of Fig.3 shows that when the kernel width gamma is 1024 and penalty factor C is 194.0117, the classification accuracy is the highest, and the model is the best.

3.3 Simulation results

SVM model was verified by test samples, the result was showed in Fig.4. A 300 samples were tested，each state consists of 60 samples, the red solid point is the diagnostic result, and the blue plus sign is the actual result.

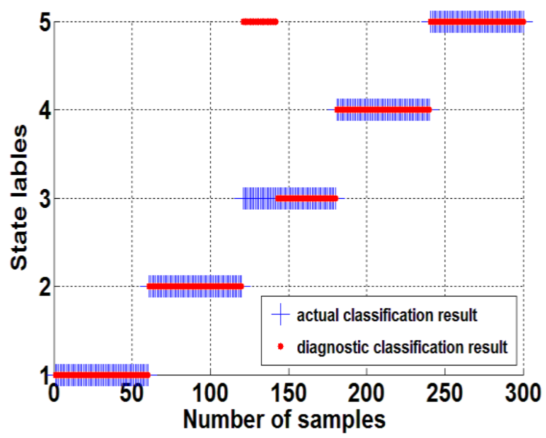

Fig.4 the result of actual and diagnostic classification.

As is shown in Fig.4, the diagnostic results of normal state, LOCA, SGTR and IRW are all correct, while the 22 samples of MSLB are wrongly diagnosed as IRW. Diagnosing correct rate of SVM model is 92.667%, illustrates that diagnosis method of SVM can reach higher accuracy.

3.4 Effect analysis of DBN extracting features

To verify the effect of DBN extraction features, feature data extracted from DBN was processed by principal component analysis (PCA), to extract principal components, and two-dimensional scatter plot, as drawn in Fig.5.

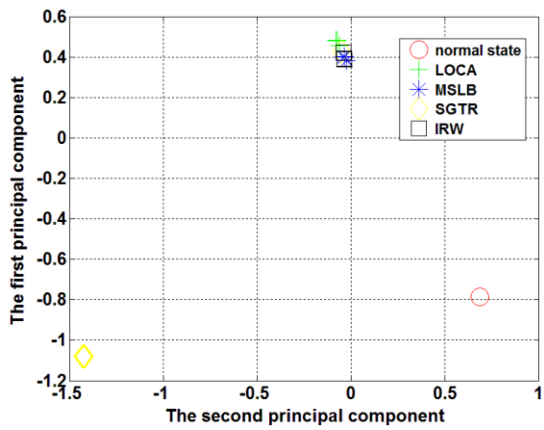

Fig.5 Principal component and scatter plot of features extracted from DBN.

As is shown in Fig.5, there are many scatter plots of MSLB and IRW coinciding. It leads to SVM confuse some samples of MSLB with IRW. Thus, instead of desired effect, the DBN extracting features is not perfect. The fault diagnosis fault of PCA extracting features was compared with that DBN extracting features in Table 3.

Table 3 Fault diagnosis results of DBN and PCA feature extraction methods

The way of extracting features	The way of fault diagnosis	Accuracy rate
DBN	SVM	92.667%
PCA	SVM	83%

The final fault diagnosis accuracy rate of DBN is higher than PCA, it indicates that the effect of DBN feature extraction from nonlinear data is better than PCA feature extraction, the method of DBN extracting features is feasible. The process of feature extraction by PCA is a process of dimensionality reduction. PCA transforms a group of variables that may be correlated into a group of linear irrelevant variables by orthogonal transformation, so as to achieve the goal of reducing the dimension of data sets. However, PCA is suitable for situations where the variables are linearly correlated and the parameters do not change with time. During the operation of nuclear power plant, the parameters are not completely linear correlation. Therefore, the effect of PCA feature extraction is not good. PCA is more suitable for feature dimension reduction after feature extraction.

4 Conclusion

The paper extracted features of operating states of nuclear power plant through DBN and established SVM diagnosis model, at last, accomplished fault diagnosis of nuclear power plant. We acknowledge the following two conclusions: First, DBN can extract features from nonlinear data, however, its effect needs to be improve. Second, the results indicate that the fault diagnosis of nuclear power plant based on DBN and SVM has feasibility and can achieve a high precision, and provides a more intelligent diagnosis method for nuclear power plant.

Acknowledgement

This research work was funded by the Natural S cience Foundation of Heilongjiang Province, Chin a (Grant NO.A2016002), the foundation of Scien ce and Technology on Reactor System D-sign Te chnology Laboratory (HT-KFKT-14-2017003), the technical support project for Suzhou Nuclear Power Research Institute (SNPI)(NO.029-GN-B-2018-C45-P.0.99-00003), and the Rese-arch Institute of Nuclear Power Operation (NO. RIN180149-SCCG).

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Appendix

List of abbreviations

Serial number	Full name	Abbreviation
1	Support Vector Machine	SVM
2	Deep Belief Network	DBN
3	Restricted Boltzmann Machine	RBM
4	Loss of Coolant Accident	LOCA
5	Steam Generator Tube Rupture	SGTR
6	Main Steam Line Break	MSLB
7	Inadvertent Rod Withdrawn	IRW
8	Principal Component Analysis	PCA