Research on Fault Diagnosis Method of Coolant System in Nuclear Power Plant

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Abstract: Coolant system is one of the most important systems in nuclear power plant. The safety and stability of the system is the basis of the stable operation of the whole nuclear power unit. Firstly, the typical fault characteristics of the system are introduced. In order to improve the accuracy of fault diagnosis, an expert diagnosis method based on sparse coding is proposed by fusing the sparse coding fault diagnosis results with the expert system. The results show that the method can extract fault feature information effectively. The accuracy of expert system for fault diagnosis of coolant system is 87.5%. After sparse coding fusion, the accuracy of fault diagnosis is increased to 94.4%. The validity and reliability of the system are verified, which can provide reference for safe operation and decision-making of nuclear power plant.

1. Introduction

Nuclear power has the characteristics of clean, efficient, economic and sustainable supply, and is the representative of future energy. Because nuclear power generates electricity by using the huge energy generated by nuclear fission, the safety requirements of unit equipment are particularly stringent [1]. Once a failure occurs, it will have very serious consequences. State monitoring and fault diagnosis play an important role in ensuring the safety and reliability of nuclear power plants. The traditional nuclear power equipment monitoring usually adopts threshold monitoring method, which can detect faults by alarming equipment parameters [2]. It can provide the operation parameters and working status of equipment for staff. However, this method cannot find the root cause of the accident, nor can it predict the development trend of abnormal state, which has certain limitations. Therefore, it is of great significance to design an effective method for monitoring and fault diagnosis of nuclear power equipment.

Based on this, in order to further improve the accuracy of fault diagnosis and ensure the safe and efficient operation of nuclear power units, this study combines sparse coding method with expert system, designs a joint fault diagnosis model based on expert system and sparse coding, and uses cold technology to solve the shortcomings of traditional fault diagnosis methods. As an example, the effectiveness and reliability of the fault diagnosis system are verified by typical faults, which can provide reference for safe operation and decision-making of nuclear power plant.

2. Fault Analysis of Main Coolant System in Nuclear Power Plant

2.1 Working principle

The main coolant system, also known as the reactor coolant system, is the primary loop main system of the nuclear power plant, and is also the core part of the nuclear power plant. It is a closed cooling loop composed of reactor, steam generator, coolant pump, regulator, pipeline, valve and other equipment, as shown in Figure 1. The main function of the main coolant system is the transformation and transfer of energy, which takes away the heat generated by the nuclear fission of the reactor. At the same time, it also plays the role of cooling the reactor and preventing the leakage of radioactive materials. During the operation of a power plant, a controllable chain reaction of nuclear fuel in the reactor releases a large amount of heat energy. Coolant absorbs heat energy in the reactor. When the heat-absorbed high-temperature coolant flows through the steam generator, it will heat transfer with the steam generator's feed water pipeline, transfer heat out, and make it vaporized into steam to drive the steam turbine to work. And generate electricity. After the coolant exothermic

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is completed, it will flow back to the reactor to continue to absorb heat, so that the cycle of heat absorption and exothermic, forming a closed cooling loops [3].

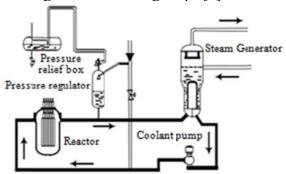


Fig.1 Principle of main coolant system

2.2 Typical Faults and Characteristic Information

The realization of the overall function of the reactor coolant system should be based on the normal operation of the functional equipment. Once the function of the equipment fails, the function of the whole system may not be realized and the reactor coolant system will fail. Coolant system faults mainly include pipeline rupture, leakage and loss of current, and the main fault characteristics are shown in Table 1.

Tab.1 Main Fault Characteristic Information of Main Coolant System

Fault name	Fault characteristics		
T WOIL HOME	Pressure drop in main circuit		
LOCA-Rupture of primary circuit pipeline	Increased temperature in cabin		
	Increased cabin pressure		
	Increased water level in cabin		
	Water level drop of regulator		
	Increased level of radioactivity in cabin		
Breakage of U-tube of steam generator	Increased radioactivity level in secondary		
	circuit		
	Pressure drop of regulator		
	Water level drop of regulator		
	Elevated levels of excreta radioactivity		
Damage of fuel cladding	Increased radioactivity level in primary circuit		
Leakage of main loop valve body	Loop Flow Decline		
Leakage of left loop steam generator	Radioactivity in the left loop		
pipeline			
Leakage of Steam Generator in Right Loop	Radioactivity in the right loop		

3. Analysis of Fault Diagnosis Expert System

Coolant system is the core component of the whole nuclear power plant system. There are many types of equipment in the system and a large amount of data to be monitored. It is difficult to select appropriate parameters to represent a fault in a large amount of data. At the same time, a fault feature may correspond to several fault types, and a fault may also be caused. Many kinds of symptoms bring some difficulties to fault diagnosis itself. It can be seen that coolant system faults usually have the characteristics of complexity and uncertainty. It is necessary to design an efficient and feasible fault monitoring and diagnosis expert system.

Coolant system fault diagnosis expert system is mainly composed of condition monitoring module and fault diagnosis module, as shown in Figure 2. The condition monitoring unit collects the running state and parameters of the equipment in real time through certain measurement and

monitoring methods, and stores the physical parameters such as pressure, flow, water level and temperature in the dynamic database. The fault diagnosis unit reads the relevant monitoring parameters from the dynamic database for analysis and processing. When the parameters are abnormal, the abnormal characteristic parameters are stored in the abnormal parameter information table, and the fault diagnosis unit is triggered. The fault diagnosis unit integrates the abnormal parameter information with the knowledge in the known fault knowledge base, and then judges the running state of the equipment according to the unified fault coding. The diagnosis results are saved in the fault information table, and the alarm is sent out on the human-machine monitoring interface. At the same time, the corresponding diagnosis strategies are given to provide the basis and decision-making for fault diagnosis.

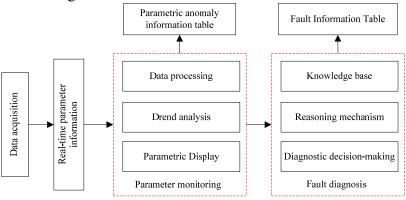


Fig.2 Fault Diagnosis Process

4. Design of Fault Expert Diagnosis System Based on Sparse Coding

4.1 Expert System Model

Knowledge base and inference engine are the most important components of expert system. The task of knowledge base is to express and store the knowledge and experience of fault diagnosis experts of nuclear power system in a specific form, so as to facilitate the reading and calling of the system. The function of inference engine is to translate expert's experience into the language that can be operated by machine, diagnose the fault of nuclear power system according to the input parameters, and output the result of fault diagnosis. The model of fault diagnosis expert system is shown in Figure 3.

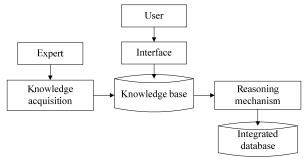


Fig.3 Expert System Model

1) Knowledge base

In the process of expert system fault diagnosis, the more abundant data are used for fault diagnosis, that is, the more fault information input, the higher the accuracy of fault diagnosis results. This is because the fault information is a description of the fault. The more specific the description is, the more accurate the fault diagnosis is and the more specific the description of the fault is.

2) Inference engine

The reasoning ability of expert system directly affects the efficiency and accuracy of fault diagnosis. Traditional expert systems adopt a single fault diagnosis strategy, which is prone to conflict in parallel diagnosis of multiple faults, leading to diagnostic errors. By combining the

neural network with expert system, the inference can be accomplished through the numerical operation function of the neural network, which can give full play to their respective advantages and make the fault diagnosis results more accurate. According to the fault characteristics of nuclear power system, the reverse reasoning strategy based on neural network is adopted. The collected fault information is imported into the inference engine through knowledge acquisition module. Then, according to the output of the neural network, the forward uncertainty reasoning is carried out, and the reasoning trajectory is recorded. Finally, the two parts of reasoning results are compared. If the reasoning results are inconsistent, data fusion is needed to improve the reasoning accuracy [4-5]. The reasoning process is as follows:

Step1: The collected fault data are imported into the knowledge base, and the fault data can be expressed as:

$$\mathbf{x} = \{x_1, x_2, \dots, x_L\} \tag{1}$$

Step2: Computational neural network implicit layer output.

$$y_{1} = \frac{1}{1 + e^{-\beta_{1}}}$$

$$\beta_{1} = \sum_{i=1}^{L} x_{i} w_{ij}^{(1)} - \theta_{i}^{(1)}$$
(2)

Step3: Calculating the output of neurons

$$y_{2} = \frac{1}{1 + e^{-\beta_{2}}}$$

$$\beta_{2} = \sum_{i=j}^{L} y_{i} w_{ij}^{(2)} - \theta_{i}^{(2)}$$
(3)

Step 4: According to the rule of fault judgment, the result of fault diagnosis is obtained.

4.2 Sparse Coding Fault Diagnosis

Sparse coding fault diagnosis can be divided into two parts: dictionary learning and sparse solution. Dictionary learning is a process of self-adaptive learning based on fault data. Sparse solution is a process of solving sparse coefficients through optimal solution method on the basis of self-adaptive learning. This paper adopts K-SVD dictionary learning method. This method trains and learns dictionary by iteration algorithm, which has the characteristics of fast training speed and strong compatibility. The learning process of K-SVD algorithm dictionary is as follows:

$$\min_{D,X} \left\{ \left\| Y - DX \right\|_F^2 \right\} \tag{4}$$

Where: D -Dictionaries, X -Sparsity coefficient, Y -Fault signals that need to be decomposed.

5. Testing and analysis

According to the above analysis, a joint fault diagnosis model based on expert system and sparse coding is designed, as shown in Figure 4.

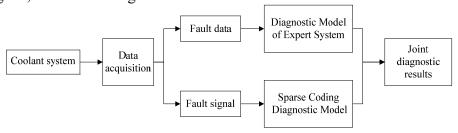


Fig.4 Joint Diagnosis Models of System Faults

After dictionary learning and sparse solution for different fault types, a complete dictionary

library is obtained, and then correlation calculation of fault signals is carried out to realize fault identification. In the process of solving, the sparsity is 15 and the maximum iteration is 60 times. After learning the dictionary based on K-SVD, a dictionary is obtained, which corresponds to eight fault types of coolant system. In order to verify the performance of sparse coding and expert system fault diagnosis proposed in this paper, the fault data of a certain agricultural machinery hydraulic system are tested, and the test results are shown in Table 2.

Tab.2 Fault diagnosis results

Fault type	Number - of samples	expert system		Sparse Coding Expert System	
		Correct	Correctness	Correct	Correctness
		Number	rate /%	Number	rate /%
Main pipe rupture	20	18	90	19	95
U-tube breakage	20	18	90	19	95
Stator leakage	20	17	85	18	90
Safety valve leakage	20	17	85	19	95
Main pipe valve leakage	20	18	90	20	100
Electric Heater Burning	20	18	90	19	95
Coolant pump power off	20	17	85	19	95
Hydraulic clamping	20	17	85	18	90
Population	160	140	87.5	151	94.4

The results show that the fault diagnosis system can effectively identify the coolant system faults. Compared with the single diagnosis method, the sparse coding based joint fault diagnosis expert system has higher recognition accuracy, reaching 94.4%, which verifies the validity of the model.

6. Conclusions

In this paper, the monitoring and diagnosis methods of reactor coolant system fault are studied. Aiming at the problems of traditional fault diagnosis methods, a joint fault diagnosis model based on expert system and sparse coding is proposed, and typical fault features are used for test and analysis. The results show that the combined fault diagnosis model can effectively realize the functions of fault data acquisition, analysis, alarm and diagnosis, and the test accuracy rate reaches 94.4%, which shows that the method is effective and feasible.

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