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Improved methods of online monitoring and prediction in condensate and feed water system of nuclear power plant

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ABSTRACT

Faults or accidents may occur in a nuclear power plant (NPP), but it is hard for operators to recognize the situation and take effective measures quickly. So, online monitoring, diagnosis and prediction (OMDP) is used to provide enough information to operators and improve the safety of NPPs. In this paper, distributed conservation equation (DCE) and artificial immunity system (AIS) are proposed for online monitoring and diagnosis. On this basis, quantitative simulation models and interactive database are combined to predict the trends and severity of faults. The effectiveness of OMDP in improving the monitoring and prediction of condensate and feed water system (CFWS) was verified through simulation tests.

1. Introduction

Nuclear power plants (NPP) are complex engineering systems which have great potential dangers (IAEA, 2013). If accidents occur during the operation, operators have to recognize the condition of NPP and take effective measures quickly and accurately (Rao et al., 2000). Unfortunately, operators may be prone to take incorrect measures due to the complexity of accidents and urgency of time (Shigetoshi, 2011). In order to provide enough information to operators during abnormal conditions and improve the safety of the NPP, it is necessary to develop the technology of online monitoring, diagnosis and prediction (OMDP) (IAEA, 2013).

Large numbers of knowledge-based and data-driven methods have been studied, but they cannot meet the requirements of practical applications (Gross et al., 1997). The most significant advantage of knowledge-based methods is making full use of experience and knowledge to avoid building complicated mathematical models (Upadhyyaya et al., 2003). But it is difficult to acquire the knowledge. Additionally, there may be many conflicts during knowledge-based reasoning processes (Ma and Jiang, 2011). For data-driven methods, the reusability and fault tolerance of these methods are much better than others. But data-driven methods overly rely on data analysis that are impossible to acquire enough data of every state. In addition, diagnosed results are hard to be explained and confirmed (Santosh et al., 2009).

Model-based methods can delve into the mechanism of equipment and systems that are easy to be understood (Jiang et al., 2014). Shigetoshi (2011) in Tokyo Electric Power Company and William and Beere (2005) in Halden Project utilize mass and energy conservation equations which will be changed to warn operators when the equipment turns to abnormal conditions. Tang et al. (2006) in Tsinghua University utilizes qualitative mass and energy equations to diagnose faults. But the model-based methods highly depend on the precision of modeling. More importantly, the parameters required in conservation equations may not be acquired in NPP.

It is clear that each method above has apparent merits and demerits. As a result, abnormal conditions cannot be monitored and diagnosed by using a single method (Ma, 2011). Therefore, the efficiency of monitoring and diagnostics will be greatly improved by the combination of different methods (Liu et al., 2014). Besides, the difficulty will be decreased and the safety will be improved with distributed strategies (Yan et al., 2009; Zhu et al., 2011).

With the rapid development of simulation and computer technology, trends prediction of faults and abnormalities are considered on the basis of online monitoring and fault diagnosis (Kondo, 1984). But the technologies of trends prediction are still in infancy. Idaho Laboratory in America first proposed thoughts of predicting the situation of NPPs by using advanced nuclear, thermal hydraulic and electrical simulation models in 2011 and the research is still ongoing until 2019 (Idaho National Laboratory, 2010).

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At present, parts of trends prediction which are mainly focus on reactor core have been used in America, France and Canada (Wang and Li, 2003). Westinghouse Company developed a system called BEACON which can do OMDP. But the trends prediction of thermal hydraulic processes such as primary reactor coolant system or secondary vapor-water hydrodynamic circulation are still difficult for the interaction of parameters and systems (Enrico and Francesco, 2010).

In this paper, the object is condensate and feed water system (CFWS) of Fangjiashan 650 MW pressurized water reactor in China. After detecting the abnormal units by online monitoring and diagnosis based on distributed conservation equation (DCE) and artificial immunity system (AIS), the trends and severity of the abnormal parameters can be predicted by condition prediction module based on quantitative simulation models. Meanwhile, the accuracy of monitoring and diagnosis can be verified by simulation models. The flow chart of OMDP is shown in Fig. 1.

The paper is organized as follows. Section 2 provides a description of distributed monitoring and diagnosis units. Section 3 presents the trend prediction module based on simulation models. The results of simulation experiment are described in Section 4. Section 5 presents the concluding remarks for this paper.

2. Distributed online monitoring and fault diagnosis module

2.1. Online monitoring based on DCE

CFWS is divided into condenser sub-unit, low-pressure heater sub-unit, deaerator sub-unit, feed water pump sub-unit and high-pressure heater sub-unit according to the distribution of the sensors (Li and Upadhyaya, 2011). Mass conservation equations are mainly used while the flow measurements in each sub-unit are complete. Meanwhile, energy conservation equations are used to monitor heat transfer processes as supplement. If the flow measurements in each sub-unit are uncompleted, energy conservation equations are mainly used. Sequentially, two-level threshold alarms are used to detect the abnormal sub-unit which can prevent ignored and incorrect alarms. While the parameters exceed one-level limits and have trends of deterioration or the parameters directly exceed two-level limits, the alarm signals will be triggered and fault diagnosis based on AIS will be active.

This paper takes low-pressure heater sub-unit as an example to illustrate the theory. From Fig. 2, the inlet extraction flow, temperature and pressure in shell side of No. 2 low-pressure heater sub-unit can be measured. But the outlet flow, temperature and pressure in shell side cannot. Meanwhile, the outlet flow, temperature and pressure in tube side can be acquired. But the inlet flow, temperature and pressure cannot as well. Therefore, No. 2 low-pressure heater sub-unit cannot be monitored separately. As well as No. 1 low-pressure heater sub-unit. As a result, they have to be combined to one unit.

If this sub-unit is abnormal, the differences between the inlet and outlet flow in shell side or tube side will be increased. However, while this sub-unit is in normal and other sub-units go wrong, the differences between inlet and outlet are very small (ASME, 2010).

The heat transfer process can be monitored according to the following energy conservation equation:

$$H_{2,out} = \left[G_{1,in}H_{1,in} + (G_{l,2}H_{l,2} - G_{l1}H_{l1})\eta\right]/G_{2,out} \tag{1}$$

where

$G_{1,\mathrm{in}}$, $H_{1,\mathrm{in}}$ – inlet flow and enthalpy of tube side in No. 1 LPHS.
$G_{2,\mathrm{out}}$, $H_{2,\mathrm{out}}$ – outlet flow and enthalpy of tube side in No. 2 LPHS.
$G_{l,2}$, $H_{l,2}$ – inlet flow and enthalpy of shell side in No. 2 LPHS.
G_{l1}, H_{l1} – outlet flow and enthalpy of shell side in No. 1 LPHS.
η – heat transfer efficiency.

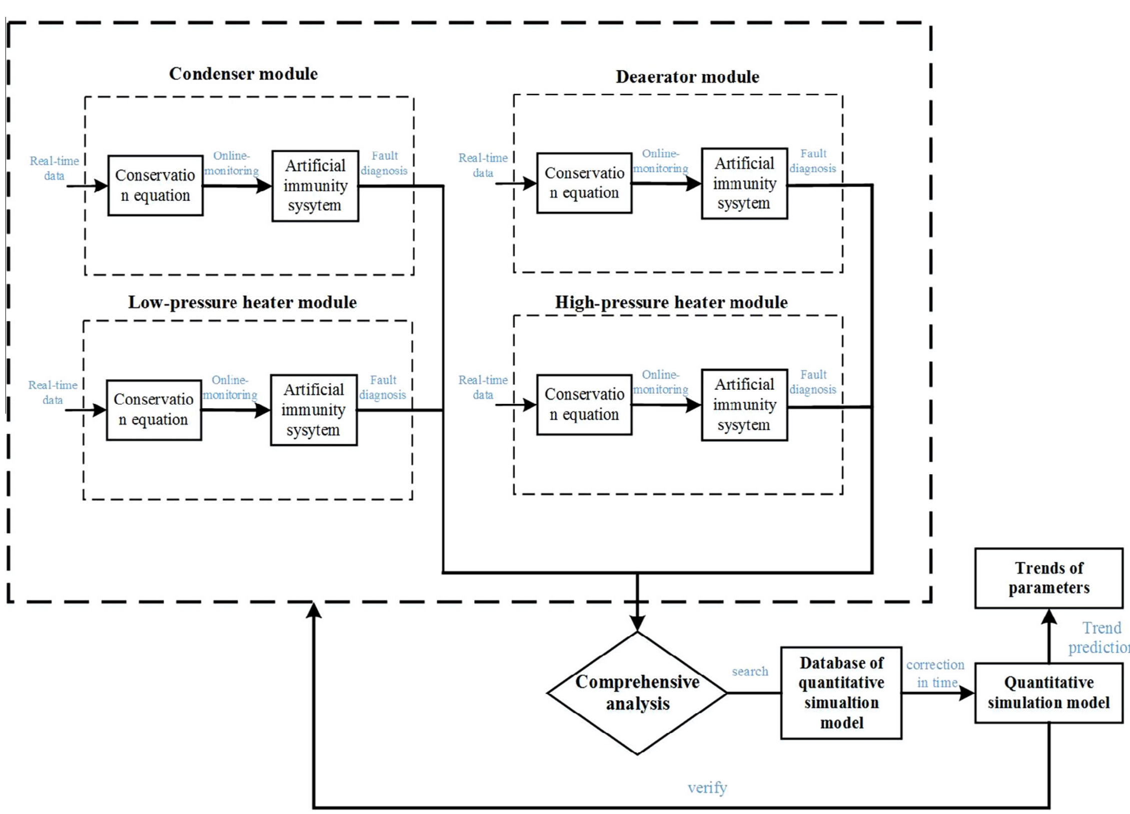

Fig. 1. Flow chat of OMPD in CFWS.

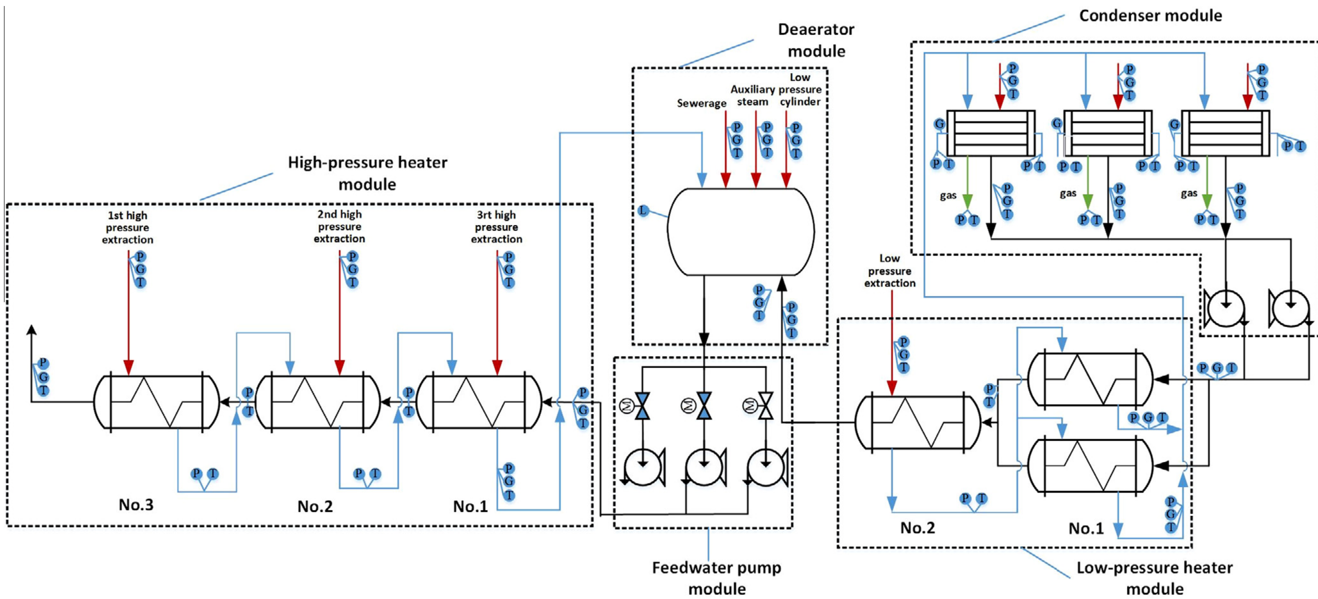

Fig. 2. Layout and distribution of measurements in CFWS.

The outlet temperature of tube side in No. 2 low-pressure heater sub-unit can be calculated by the enthalpy in Formula (1). So the low-pressure heater sub-unit can be monitored by comparing with the real measurements.

The parameters of condenser sub-unit, deaerator sub-unit, feed water pump sub-unit and high-pressure heater sub-unit can be monitored according to the layout of measurements as shown in Table 1.

2.2. Fault diagnosis based on AIS

Fault diagnosis is based on the model of antigen and antibody mutual recognition which is a branch of AIS (Dasgupta et al., 2011). The module runs online when the abnormal conditions are detected by DCE. Diagnosed results will be calculated efficiently for the trends prediction module and can be verified with each other.

AIS is a data-driven method developed in recent years (Zhang et al., 2007). The advantages of AIS such as distributed, self-adaption, self-organization and self-learning provide a method to solve the problems of diagnosis. AIS is a "black box" that make it hard to be explained as the same as artificial neural network. But the knowledge of artificial neural network is indicated by weights and thresholds which takes long time to train. However, AIS utilizes antigen and antibody to combine with real-time data matrix which make fault diagnosis have a faster training time and a better self-learning ability (Zhang et al., 2013).

According to the theory of AIS, the lowest binding energy is reached while the data matrix combines with the antigen and antibody of itself. And the binding energy is going larger when the data matrix is combined with the others. The model proposed by Tarakanov and Dasgupta (2000) is shown below:

$$W = -u_T M v \tag{2}$$

W means the binding energy of antigen and antibody. u, v presents the antigen and antibody. M describes the data matrix. Enough important parameters in every monitored sub-unit are used in the data matrix. The parameters in normal and abnormal conditions are transformed as matrix $M1$, $M2$ and so on. The antigen and antibody of every data matrix can be calculated by using historical data. After that, the antigen and antibody will be used to diagnose faults. The diagnostic procedure is shown in Fig. 3 which can be divided into three steps:

Step1: Average and normalization of data. Fault samples are indicated as $X_{ij} = (x_{ij1}, x_{ij2}, \ldots)$, where i means fault types, j means the different groups of every group. 1, 2 mean the number of

Table 1
Monitored parameters of each unit.

Units	Parameters
Condenser	Condensate outlet temperature Pressure drop between inlet and outlet of condensate pump
Low-pressure heaters	Difference between inlet and outlet flow in tube side Difference between inlet and outlet flow in shell side Outlet temperature of tube side
Deaerator	Level of deaerator Outlet temperature of deaerator
Feed pump	Pressure drop between inlet and outlet
High-pressure heaters	Difference between inlet and outlet flow in tube side Difference between inlet and outlet flow in shell side Outlet temperature of tube side

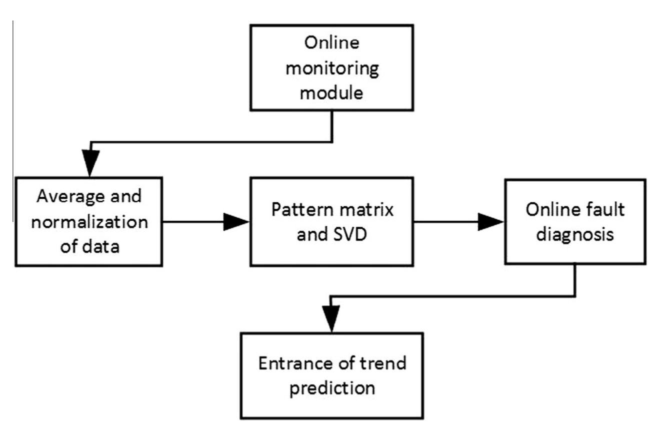

Fig. 3. Diagnostic procedure based on AIS.

parameters. The different groups of every sample must be averaged and then data should be normalized to $[0-1]^n$.
Step2: Structure data matrix and singular value decomposition. The averaged samples are folded into data matrix. If the data cannot be folded into square matrix, zero is added at the last of the data matrix. Singular value decomposition must be done to the data matrix for getting its antigen and antibody.
Step3: Online fault diagnosis. After normalizing real-time data, the binding energy can be calculated separately by connecting the antigen and antibody with real-time data matrix. In this way, the most possible fault will be diagnosed.

3. Trends prediction based on simulation models

If the system is in normal, the current state can be simulated by simulation models in real-time. While the failure occurs, the future states and trends of systems or equipment can be predicted by simulation models. The flow chat is shown in Fig. 4. This module contains real-time database, offline simulation database and simulation models which can be seen from Fig. 4. DCE module can be verified by simulation models while the system is in normal. More importantly, results of AIS can be proved by the prediction results. Clearly, the safety and reliability of CFWS will be increased (Hartner et al., 2005).

3.1. Simulation modeling of CFWS

According to the characteristics of the system, high precision model must be established in order to ensure the accurate simulation of faults or accidents (Chadha and Welsh, 2000). In this paper, the numerical simulation of CFWS which involves major general and special faults is modeling with Fortran programming. After simulation modeling of each equipment, the corresponding input and output parameters of every equipment such as condenser, LPHS, deaerator and so on are connected with each other. As a result, the simulation models of CFWS must run stability with control system. Deviations between the simulated parameters and measured parameters should be within the threshold.

3.1.1. Simulation algorithm

The numerical simulation of condenser, LPH, deaerator, HPH and FWP is the important parts of CFWS. Dynamic inputs parameters will be received, and then the dynamic outputs can be calculated by simulation models. In order to meet the requirements of real-time or even faster than real-time simulation, this paper utilizes Adams method which is one of the liner multi-step methods. Its basic idea is to simulate the function value $f(t, y)$ by interpolation polynomial. In this method, the value of y_{i+1} can be calculated by the values before t_i which can be stored in memory. That means the value of y_{i+1} will be calculated in real-time or faster than real time (Wu et al., 2005).

3.1.2. Test and connecting of sub-units

Considering the flow processes of whole system, the outputs and inputs outside of the system such as turbine exhaust flux, extraction flow of steam must be acquired from the real one and transmitted to the system. After that, no matter in the different power operations or any condition of faults, control logic of real system must be get and simulated to complete the simulation of CFWS.

Static and dynamic test are done to CFWS offline. The parameters must be modified and adjusted until simulation models run stable and errors within the thresholds. Parts of the main parameters of simulated and measured parameters during 650–325 MW power reduction processes are compared in Figs. 5–8. As it is still in the phase of theoretical research, the real data cannot be get from Fangjiashan PWR. So 650 MW Fangjiashan full-scope simulator is considered as real NPP.

From Figs. 5–8, the real one and simulation models are running in 650 MW from 0 s to 120 s. Additionally, the errors of condenser, low pressure heater, deaerator, high pressure heater and feed water pump are within 2%. Power reduction starts in 120 s, and electric power of 325 MW is reached in 1500 s. After that, they are running in 325 MW from 1500 s to 2100 s. It is clear that the trends of simulated and measured values are consistent. As a result, simulation models can reflect the static and dynamic characteristics of CFWS after testing.

3.2. Initialization and correction of simulation models

Simulation models need to be modified timely by using interactive database to make it run consistent with the real one (Park and Ahn, 2010). The interactive database is divided into two parts. One called real-time database is used for acquiring and storing the parameters of real system in time. The other one is called offline simulation database which stores all the parameters in normal conditions of different electric powers offline. What is more, it also reserves all the degree of different faults or accidents which may occur in the real CFWS. Fig. 9 shows the structure and form of the offline database.

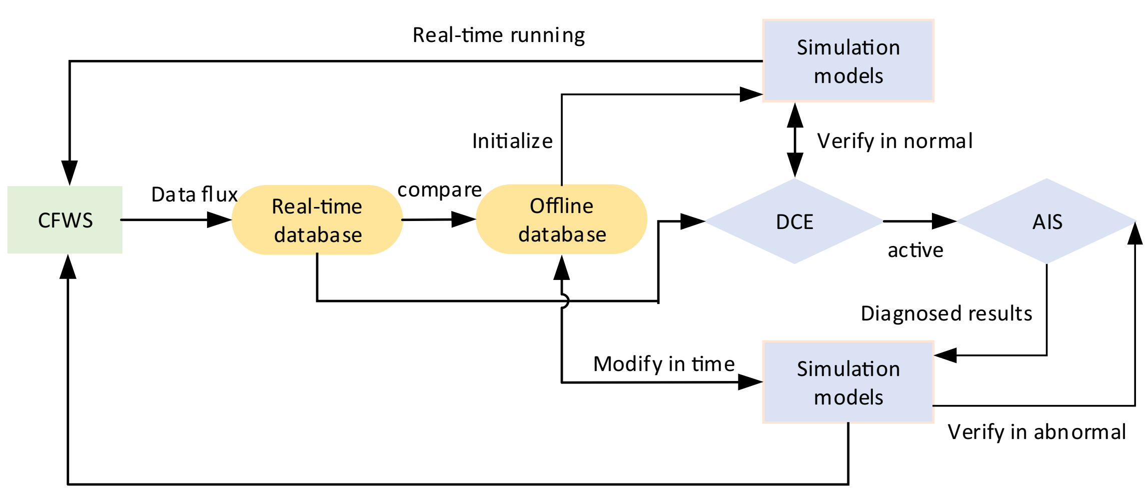

Fig. 4. The flow chat of trend prediction module.

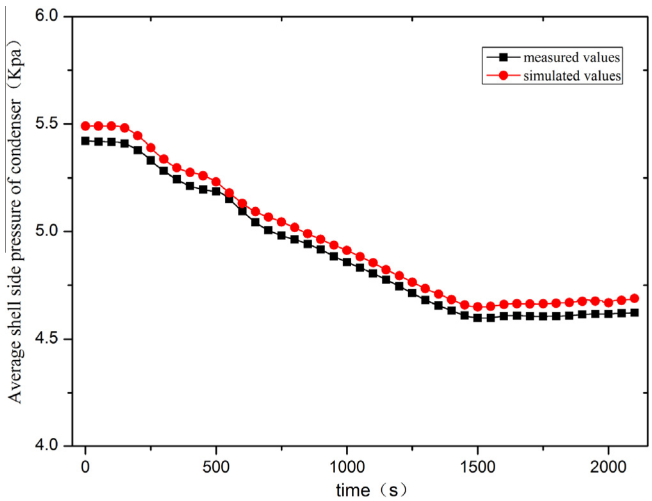

Fig. 5. Average shell side pressure of condenser.

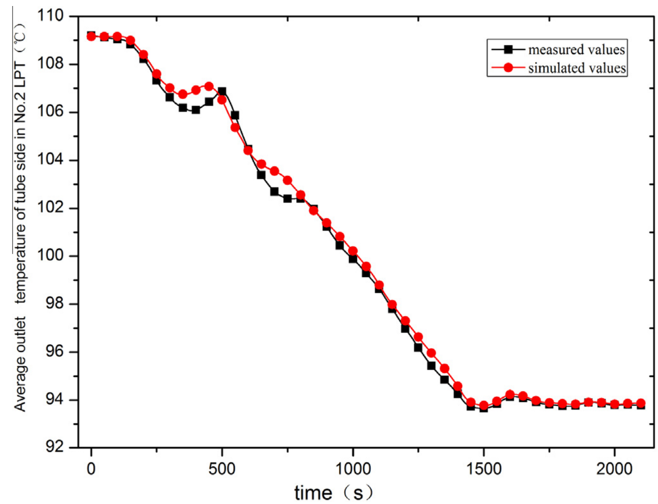

Fig. 7. Outlet temperature of tube side in No. 2 LPH.

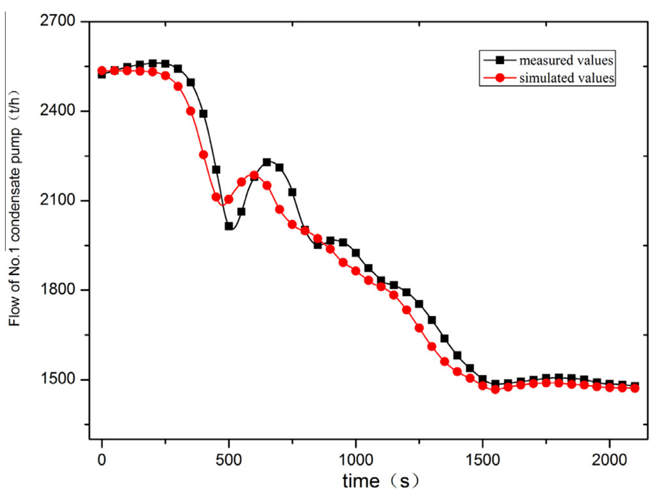

Fig. 6. Flow of No. 1 condensate pump.

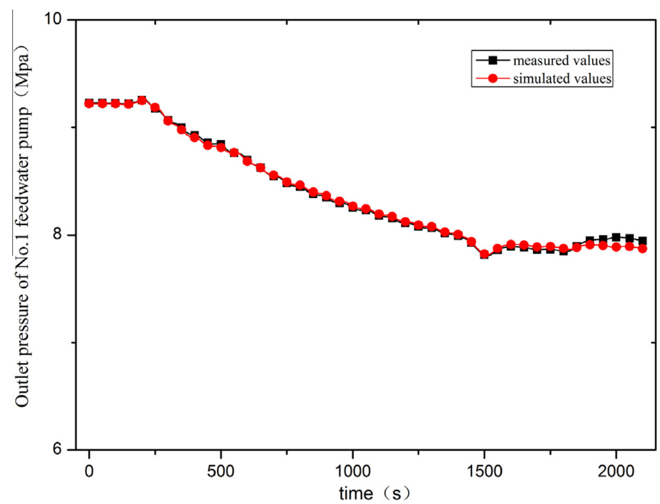

Fig. 8. Outlet pressure in No. 1 feed water pump.

Simulation models run in different electric powers offline to store the stable running condition in offline database. Simulation models choose the most similar scenario stored in offline database compared with the conditions of real system in initialization (Ahn and Park, 2009). After that, the model can be slight modified such as the correction of valves and pumps based on the DCE module (Choi et al., 2008).

While the abnormal conditions occur, simulation models are still running in normal. As a result, the measured values and simulated values will be different which means simulation models and DCE can be verified with each other. After the fault is diagnosed by AIS module, offline database puts the corresponding fault scenarios into simulation models. And the trends of parameters can be compared with the real one. If the trends are similar, this fault diagnosed by AIS module will be verified by simulation models.

For confirming the degree of faults, it is essential to take out several specific degrees of current fault which have been simulated offline and stored in offline database. The change ranges of the monitored parameter and corresponding offline simulated parameter of several specific degrees are compared by real-time database and offline database. In this way, the shrunken range of fault degree will be confirmed. Sequentially, the degree will be dynamic real-time adjusted in this range from simulation models. At last, simulation models can run faster than real-time to do the prediction of CFWS.

4. Simulation test

As the purpose of improved OMDP is used to provide online operation support and guidelines in emergency. Therefore, assuming that incipient faults do not happen or the phenomenon is not obvious. As the simulation models and real plant have errors within the acceptable limits, some small incipient faults cannot make the parameters of real plant different with the simulation models. Sudden faults which contains general and specific faults can be diagnosed and predicted. The general faults such as fail of valves and pumps or specific faults such as leakage of high pressure heater or low pressure heater, breakage of deaerator, air goes into the deaerator or condenser and so on can be diagnosed and predicted by the methods in this paper. However, the diagnosis and prediction of general faults are easier than specific faults. So one of specific faults is selected to do the simulation test. In order to help operators realize and understand the processes of this

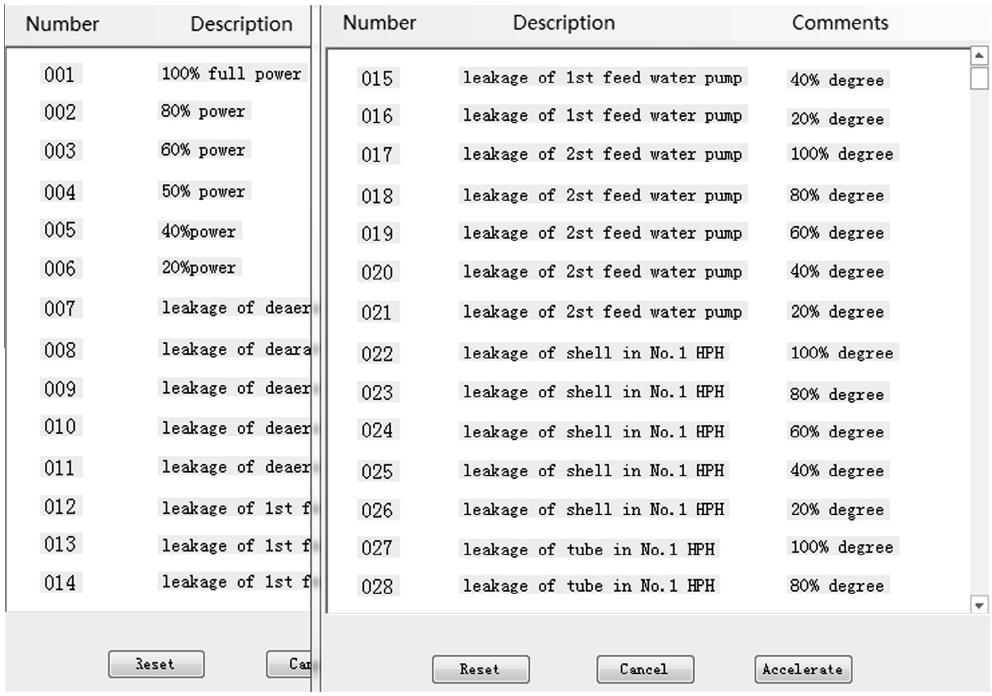

Fig. 9. The structure of offline database.

methodology, human machine interfaces are built by C# programing. As it is still in the phase of theoretical research, the real data cannot be get from Fangjiashan nuclear power plant. So 650 MW Fangjiashan full-scope simulator is considered as the real PWR. This paper assumes that real-time data is dependable which means the faults of sensors are not considered.

The leakage of cooling water pipes in the 1st condenser is used as an example for simulation test. This paper assumes Fangjiashan PWR is running stable in 650 MW full electric power and the leakage occurs at 120 s. The leakage flow is assumed as 332.38 kg/s in random and the corresponding leakage degree is 78%.

Offline database initializes in simulation models according to the real-time data to make them run consistent as shown in Fig. 10. On the bottom, main interface is shown. In the middle area, a part of offline database is shown after clicking the button "Interactive database" on the top of main interface. In the front, the selection and confirmation of resetting to the current state are shown after clicking the button "reset" on the window of offline database. At the same time, DCE module and AIS module are running in real-time. At 130 s, the condensate temperature of 1st condenser exceed one-level limit 0.35 °C and have a trend of deterioration. But deviations of condensate temperatures in 2nd and 3rd condenser, outlet temperature of tube side in low pressure heater and high pressure heater, outlet temperature of deaerator, inlet and outlet pressure of feed water pump are all within the thresholds. The results of condenser and deaerator module are shown in Figs. 11 and 12.

As the abnormal condition have been detected, AIS module runs online in time. Inlet and outlet temperature of cooling water in tube side, pressure in shell side, outlet temperature of shell side, water level of condenser, inlet and outlet pressure of cooling water in tube side, condensate flux of No. 1 and No. 2 condensate pump are selected as training parameters offline according to the characteristic of condenser. They are shown as $m1$–$m9$. Normal data and some of most possible faults are selected as data matrix. The average and normalization of data are shown in Table 2.

Averaged normal and fault samples are folded into $3 * 3$ data matrix. The results of singular value decomposition are shown in Table 3. The abnormal data of 1st condenser sub-unit getting from real-time database is averaged and normalized in time, so the binding energy can be calculated by combining real-time data matrix with every group of antigen and antibody. The diagnosed results are shown in Fig. 13.

From Fig. 13, the lowest binding energy is get by antigen and antibody corresponding to cooling water pipe leakage after 125 s. As a result, the fault is cooling water pipe leakage in 1st condenser. And then different degrees of this fault will be selected from offline database. For the reason that it is impossible to list all the degrees, only degrees of 100%, 80%, 60% and 50% are stored in offline database. The monitored parameter, condensate temperature is shown in Fig. 14. Considering about the errors of temperature measurements, the temperature sensors can only the change ranges exceed 0.1 °C can be recognized by temperature sensors. In Fig. 14, the change range of condensate temperature is 0.5 °C from 120 s to 150 s. However, the corresponding change range of 100% leakage in simulation models is 0.7 °C, 80% leakage is 0.6 °C, 60% leakage is 0.4 °C, and 50% leakage is 0.3 °C from 120 s to 150 s. The change ranges of parameters are compared and then dynamic real-time adjustments are done in simulation models of specific ranges as shown in Fig. 15.

As shown in Fig. 15, the leakage degree is within 60–80% by calculating the change range from 120 s to 150 s. After dynamic adjustment of in simulation models, the change range of 75% degree is 0.5 °C which is similar with the real one. The future trends of other important parameters of 75% leakage in 1st condenser can be calculated by in simulation models as shown in Figs. 16–19.

From these figures, it is obvious that cooling water pipeline leakage of 1st condenser in CFWS is predicted. In addition, the leakage flow is 319.60 kg/s while the real fault assumed in the simulator is 332.38 kg/s. The deviation is within 5%.

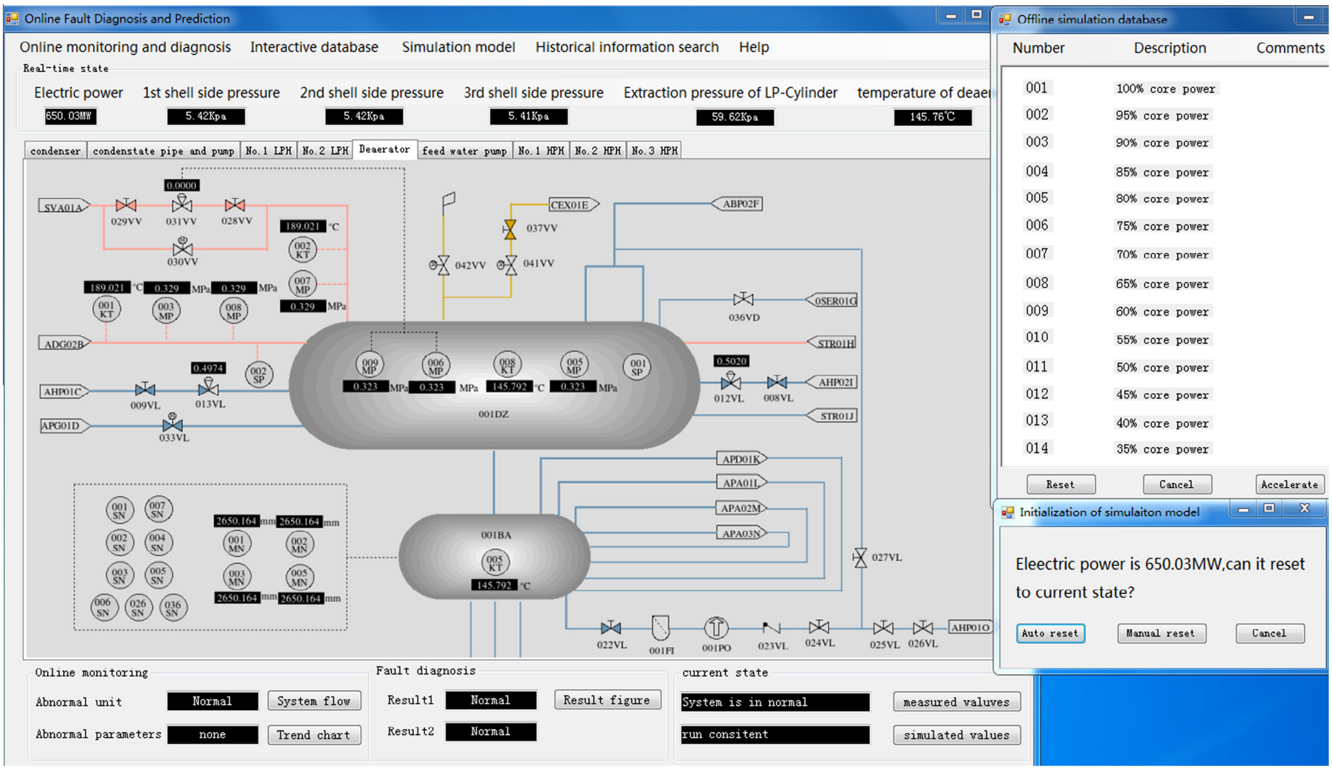

Fig. 10. Initialization of simulation models.

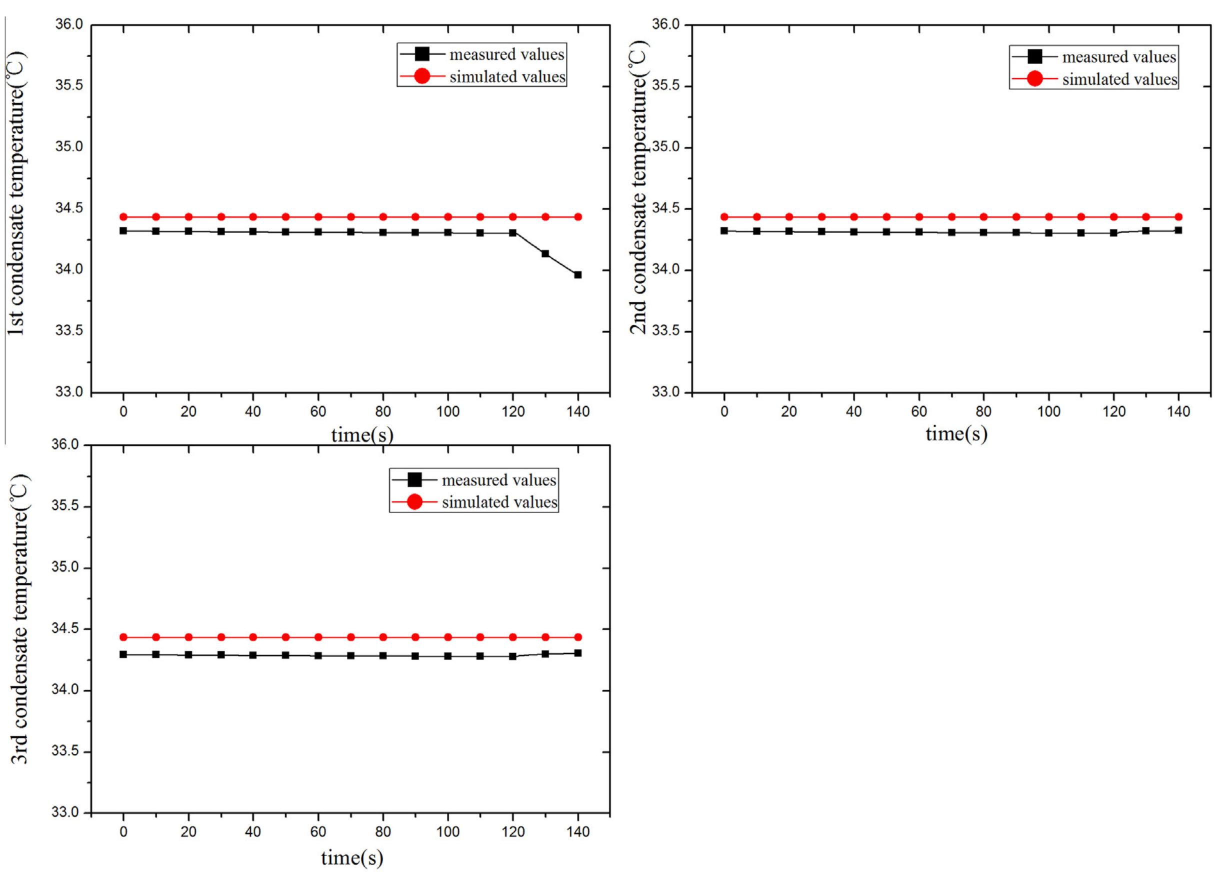

Fig. 11. Online monitoring results of condenser module.

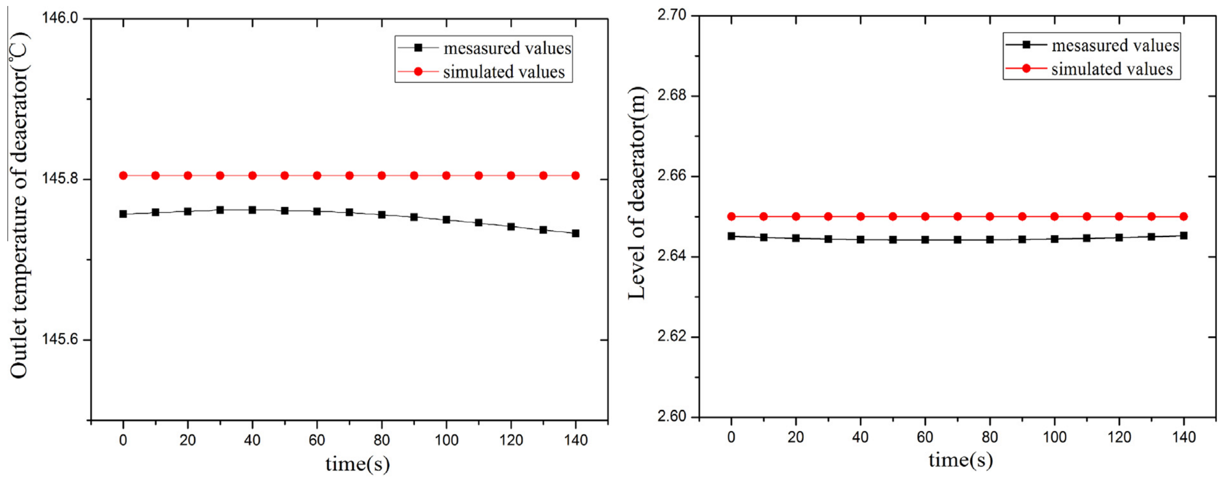

Fig. 12. Online monitoring results of deaerator module.

Table 2
Average and normalization of data.

Number	Data matrix	$m1$	$m2$	$m3$	$m4$	$m5$	$m6$	$m7$	$m8$	$m9$
1	Normal	**0.500**	**0.739**	**0.334**	**0.388**	**0.116**	**0.388**	**0.376**	**0.865**	**0.873**
2	Air into the shell side	**0.500**	**0.105**	**0.900**	**0.158**	**0.886**	**0.900**	**0.900**	**0.874**	**0.882**
3	Condensate pipe leak	**0.500**	**0.473**	**0.443**	**0.100**	**0.110**	**0.900**	**0.900**	**0.741**	**0.737**
4	Cooling water pipe leak	**0.500**	**0.872**	**0.100**	**0.900**	**0.122**	**0.270**	**0.254**	**0.871**	**0.879**

Table 3
Results of singular value decomposition.

Data matrix	Normal	Air into the shell side
Antigen and antibody	$u1$ (−0.367, −0.452, −0.813) $v1$ (−0.573, −0.441, −0.691)	$u2$ (−0.432, −0.561, −0.706) $v2$ (−0.442, −0.545, −0.712)
Data matrix	Condensate pipe leak	Cooling water pipe leak
Antigen and antibody	$u3$ (−0.466, −0.409, −0.785) $v3$ (−0.565, −0.488, −0.665)	$u4$ (−0.562, −0.412, −0.717) $v4$ (−0.508, −0.710, −0.487)

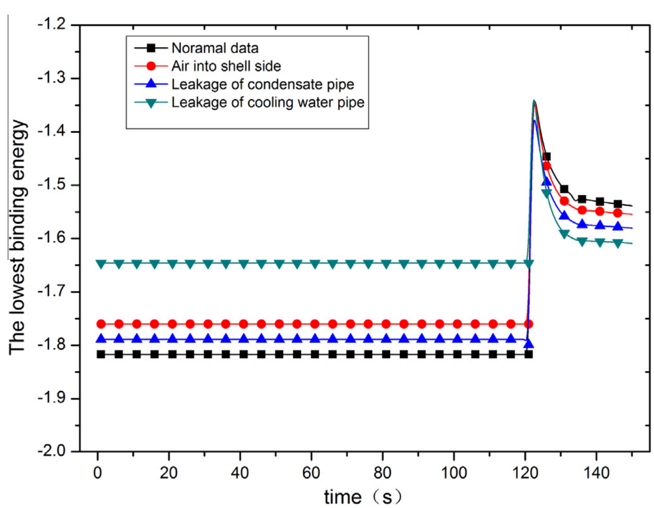

Fig. 13. The diagnosed results.

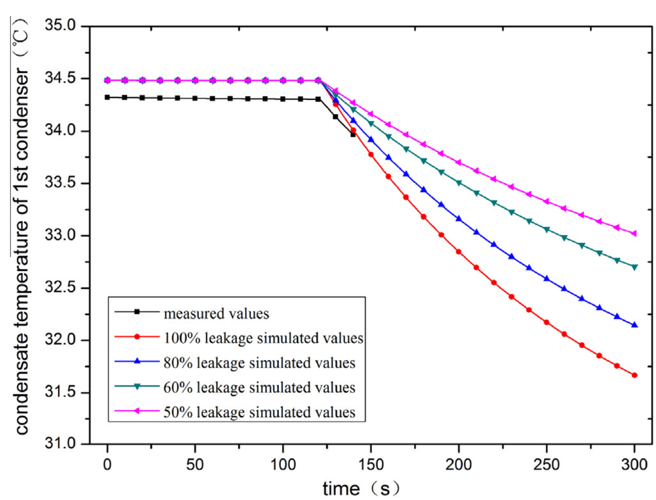

Fig. 14. Condensate temperature of in modifying.

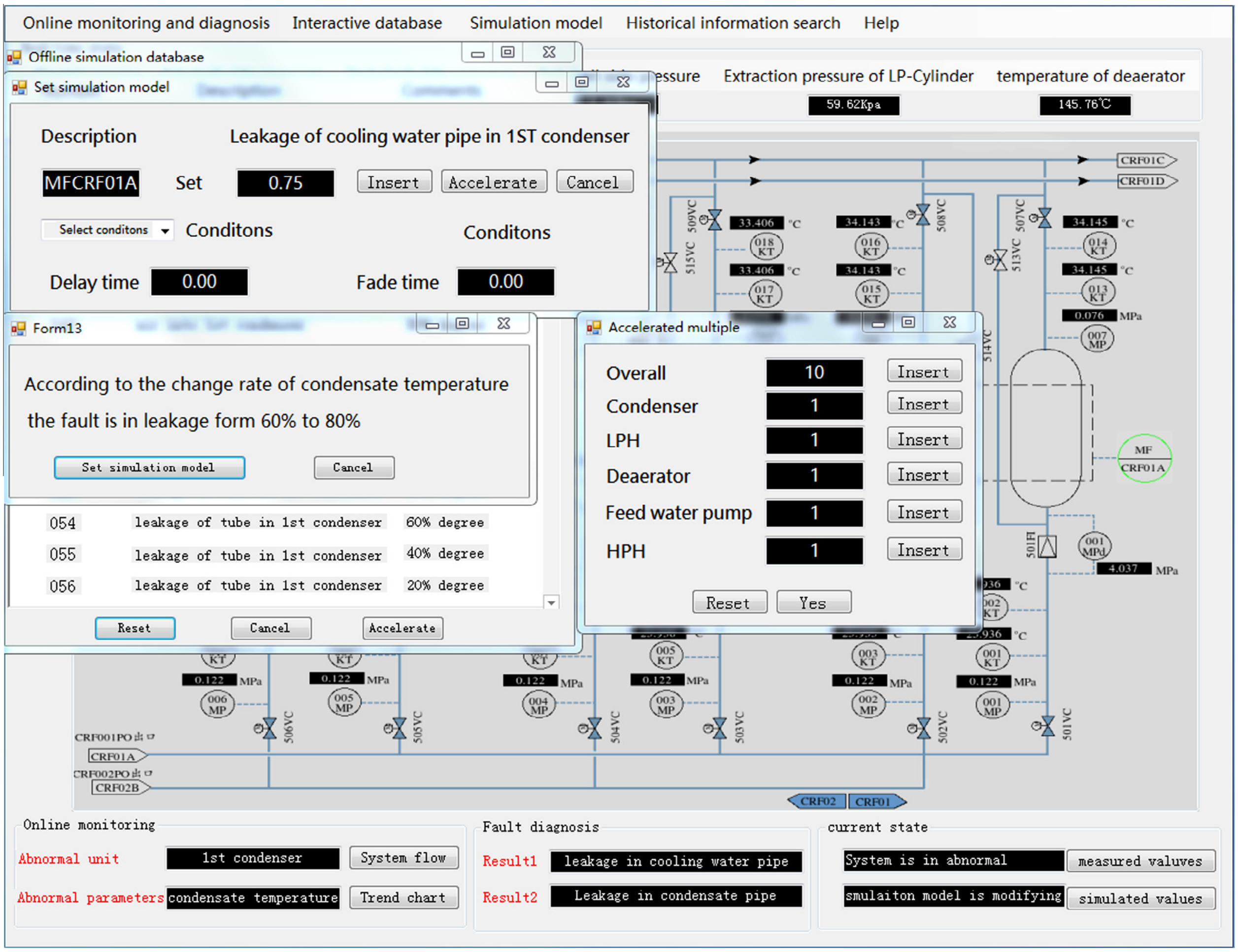

Fig. 15. Dynamic real-time adjustment in the simulation models of specific ranges.

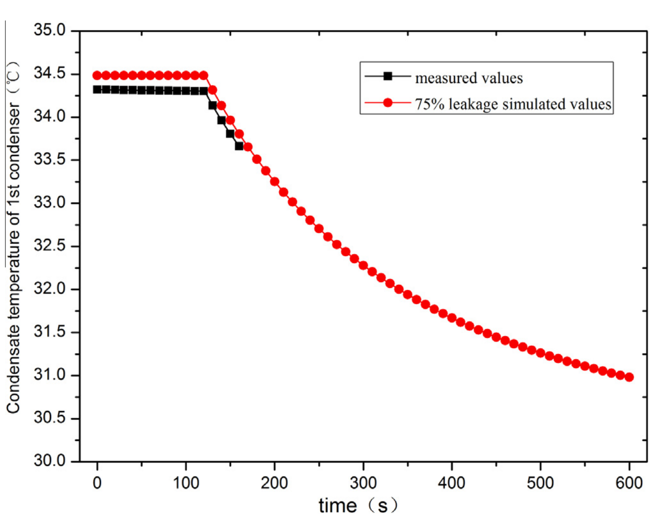

Fig. 16. Condensate temperature of 75% leakage.

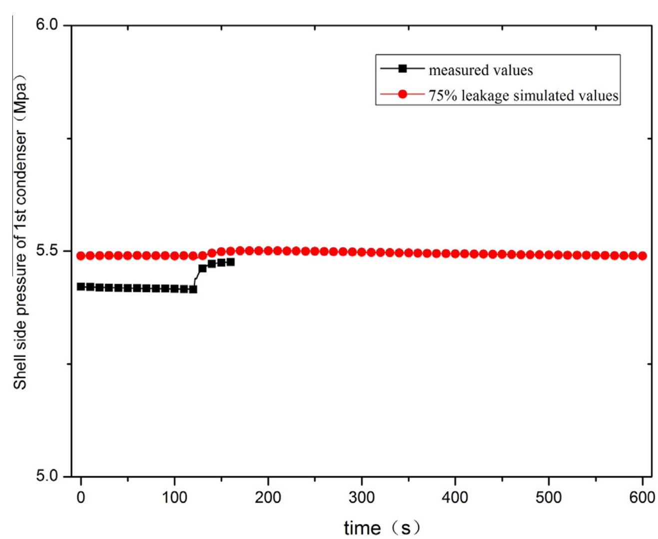

Fig. 17. Shell side pressure of 75% leakage.

In this way, faults can be diagnosed and predicted by cooperation and verification of DCE module, AIS module and in simulation models. Ignored and incorrect diagnosis will be avoided. Clearly, it is better for operators or emergency management people to realize the trends and severity of faults or accidents.

5. Conclusions

The distributed OMPD methods are proposed for improving practical application in this paper. Faults can be detected in time. Additionally, the trends and severity of faults can be predicted

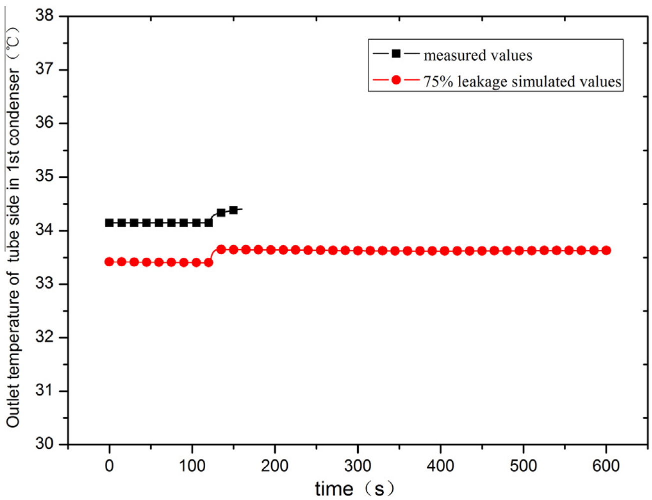

Fig. 18. Outlet temperature of tube side of 75% leakage.

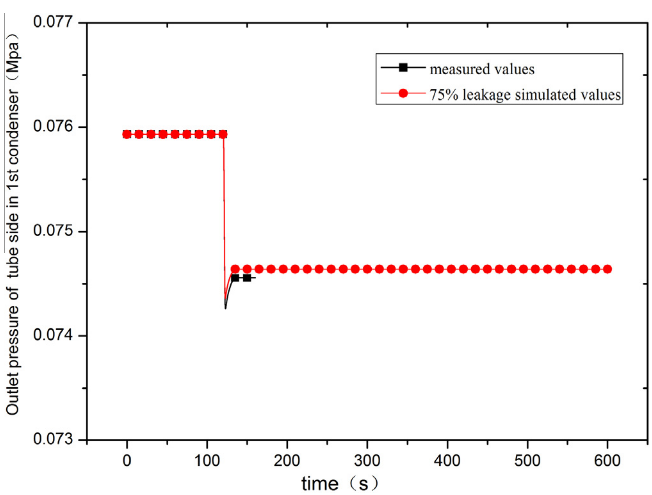

Fig. 19. Outlet pressure of tube side of 75% leakage.

accurately. Simulation tests show advantages of OMPD methods, as follows:

(1) Combined two-level thresholds and trend variation of alarms are better to detect abnormal conditions and faults.
(2) AIS is efficiency and suitable in aspects of real-time and accuracy.
(3) Simulation models can predict the trends and severity of faults in time.
(4) Simulation models, DCE and AIS can be verified with each other.

In conclusion, this methods can help operators and emergency management people in accidents. So, full-scale simulator is used as real system which is different in acquiring data. Our future work is of course to research more efficient ways to diagnosis and predict multiple faults, to predict mitigation and operation guidance and to improve the function of interactive database.

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