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Internal leakage detection for feedwater heaters in power plants using neural networks

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ABSTRACT

As interest in safety and performance of power plants becomes more serious and wide-ranging, the significance of research on turbine cycles has attracted more attention. This paper particularly focuses on thermal performance analysis under the conditions of internal leakages inside closed-type feedwater heaters (FWHs) and their diagnosis to identify the locations and to quantify leak rates. Internal leakage is regarded as flow movement through the isolated path but remaining inside the system boundary of a turbine cycle. For instance, leakages through the cracked tubes, tube-sheets, or pass partition plates in a FWH are internal leakages. Internal leakages impact not only plant efficiency, but also direct costs and/or even plant safety associated with the appropriate repairs. Some types of internal leakages are usually critical to get the parts fixed and back in a timely manner. The FWHs installed in a Korean standard nuclear power plant were investigated in this study. Three technical steps have been, then, conducted: (1) the detailed modeling of FWHs covering the leakage from tubes, tube-sheets, or pass partition plates using the simulation model, (2) thermal performance analysis under various leakage conditions, and (3) the development of a diagnosis model using a feed-forward neural network, which is the correlation between thermal performance indices and leakage conditions. Since the operational characteristics of FWHs are coupled with one another and/or with other neighbor components such as turbines or condensers, recognizing internal leakages is difficult with only an analytical model and instrumentation at the inlet and outlet of tube- and shell-sides. The proposed neural network-based correlation was successfully validated for test cases.

1. Introduction

Even though there is somewhat difference among electric power sectors, the heat generation system such as boilers or nuclear reactors seems considered more seriously than the heat conversion system utilizing, for instance, Rankine cycle from the viewpoint of not only efficiency but also safety. While the efficiency is focused on fuel management in fossil-fuel plants, the efficiency of nuclear power plants is less interesting due to the base-load operation. However, many activities, which are based on information technologies, for improving the level of efficiency as well as even safety of a turbine cycle have begun and been carried out recently. The concern for efficiency must be related to the deregulation environment in electric industry. Reducing the unit cost of electricity production becomes more important to compete with other power sources. Since it is unlikely that, particularly, the large capacity power plants get shut down during normal operation to repair equipment belonging to a turbine cycle, reducing the unit cost is practically a matter of optimizing maintenance during an outage and reducing downtime. It is obvious that the optimized maintenance should be supported by credible inspection and testing. From the safety viewpoint, the turbine cycle in nuclear power plants began to be scrutinized as well. An accident which occurred in the turbine building of the Japanese Mihama nuclear power plant in 2004 stimulated the regulatory authorities to reconsider the safety concerns of the turbine cycle. Apart from such a tragic accident, Cho and April (2007) reported that three quarters of unanticipated reactor shutdowns during the last 6 years in Korea resulted from turbine cycles. Even though a shutdown caused by a turbine cycle is not critical to nuclear safety, a large number of unanticipated shutdowns tend to threaten the integrity of nuclear safety. It should be noted that

Abbreviations: CBM, Condition-Based Maintenance; COP, condensate pump; DCA, Drain Cooler Approach; DP, Differential Pressure; FWBP, feedwater booster pump; FWH, feedwater heater; FWP, feedwater pump; HP FWH, high pressure feedwater heater; HP TBN, high pressure turbine; LP FWH, low pressure feedwater heater; LP TBN, low pressure turbine; PEPSE, Performance Evaluation of Power System Efficiency; SG, steam generator; TD, Temperature Difference; TTD, Terminal Temperature Difference; VWO, valve wide open.

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enhancing the safety of turbine cycles is also a process that must occur through inspection, testing, and maintenance during an outage.

For optimal maintenance processes supported by inspection and testing, Condition-Based Maintenance (CBM) could be considered. As introduced by the technical documents published at the International Atomic Energy Agency (2003, 2007), the goal of CBM is predictive maintenance: to optimize reliability and availability in a proactive manner by determining the need for maintenance activities based on equipment condition. Hines and Seibert (2006) and Hines, Garvey, Seibert, & Usynin (2006) summarized the benefit of the on-line monitoring techniques and the regulatory considerations for their applications, while Heo (2008a, 2008b) described the technical aspects of CBM and introduced the examples that his group had performed. This study will be another illustrative case of CBM for enhancing the efficiency and safety of a turbine cycle.

This study attempted to suggest a means of detecting the internal leakage occurring in feedwater heaters (FWHs). The detection of internal leakages in FWHs has been studied extensively but its solution is still pending. The leakage of a FWH definitely impacts the efficiency of the entire turbine cycle due to the loss of the regenerative cycle, and may increase the possibility of failure of high energy piping due to thermal shock. However, since the operational characteristics of all the components in a turbine cycle are highly coupled with each component, it is difficult to observe the anomalies taking place inside FWHs. In order to find a method for the detection and diagnosis of FWHs' internal leakages, the paper proposed a correlation model based on a neural network which has the capability of non-linear regression.

2. Characteristics of feedwater heaters

2.1. Feedwater heaters

A FWH is a component used to preheat water delivered to a boiler or a steam generator (SG). FWHs allow the working fluid to be brought up to the saturation temperature gradually. This minimizes the inevitable irreversibility associated with heat transfer, and therefore improves the thermodynamic efficiency of a turbine cycle. This reduces operating costs and also helps to avoid thermal shock to the material of the boilers or SGs. FWHs can be open and closed heat exchangers. The open FWH, also called a deaerator, is specially designed to remove non-condensable gases from working fluid. A single deaerator is normally used in Rankine cycle. The closed FWHs are typically shell-tube heat exchangers where the feedwater passes throughout the tubes and is heated by extraction steam from a shell-side. The turbine cycle of large capacity power plants has the 5–7 cascade closed FWHs which are composed of two or three trains, as shown in Fig. 1.

Since the steam extracted from turbine stages is saturated or a little superheated depending on turbine stages, three kinds of heat transfer mechanisms exist inside the FWHs: the superheating region for steam-water heat transfer while the extracted steam is superheated, the condensing region for heat transfer while the steam is saturated, and the drain cooling region of water-water heat transfer while the steam is condensed and sub-cooled. In fossil-fuel plants, both of three-region FWHs and two-region FWHs which only condensing and drain cooling regions are available are used. In case of general pressurized water reactors, only two-region FHWs are used due to main steam quality. In order to represent the thermal performance of a FWH, the following performance indices are suggested:

- Differential Pressure (DP) at tube side or shell side.
- Temperature Difference (TD) at tube side or shell side.
- Terminal Temperature Difference (TTD) = saturated steam temperature – feedwater outlet temperature.
- Drain Cooler Approach (DCA) = drain outlet temperature – feedwater inlet temperature.

If a problem happens in a FWH, the performance indices will show deviations from certain design values. For instance, internal leakage, fouling, plugging, and abnormal level control correspond to such problems, and may cause the performance indices to change. However, it should be noted that the performance indices may also change in the absence of any problems. The operational characteristics of turbine cycles are coupled with each component,

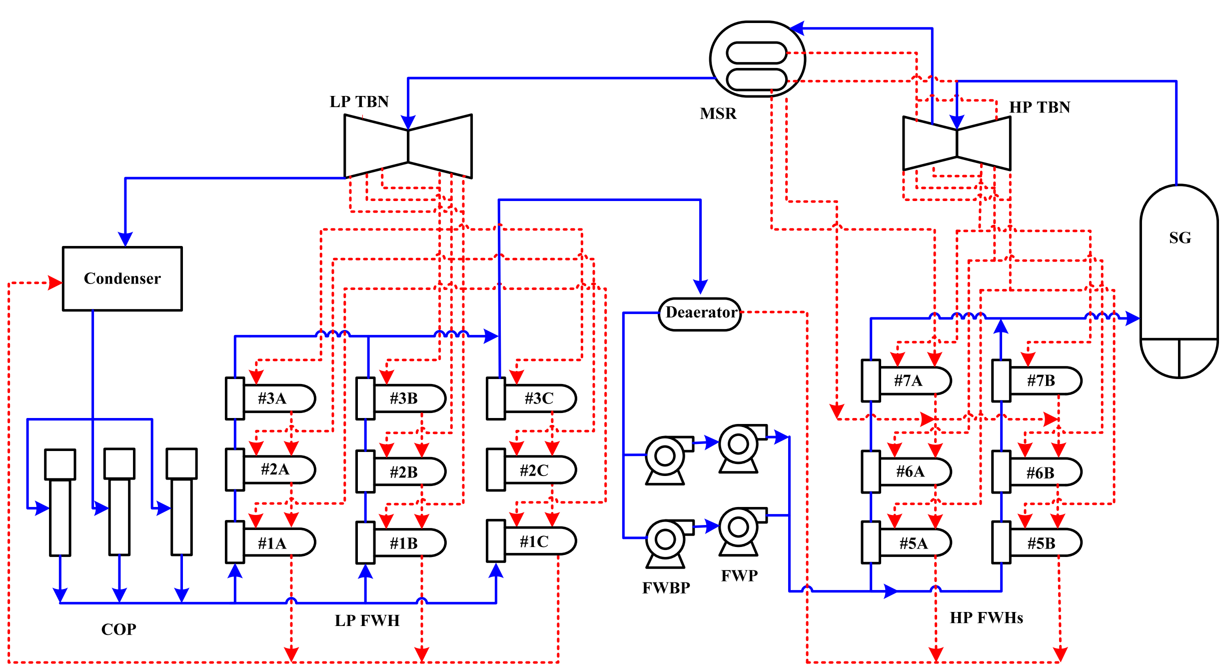

Fig. 1. Schematic diagram of the turbine cycle in Korean standard nuclear power plant (solid: main flow; dot: extract or drain flow).

Table 1
Effects of performance degradation (Upper: the heat transfer area of FWH1A decreases by 10%, Lower: the heat transfer area of FWH5A decreases by 10%).

	TTD	DCA	Tube side		Shell side	
			TD	DP	TD	DP
FWH1A	1.167	1.099	0.984	1.206	0.979	0.986
FWH1B	1.000	1.000	1.000	1.000	1.000	1.000
FWH1C	1.000	1.000	1.000	1.000	1.000	1.000
FWH2A	1.015	1.026	1.012	1.000	1.010	1.015
FWH2B	1.000	1.000	1.000	1.000	1.000	1.000
FWH2C	1.000	1.000	1.000	1.000	1.000	1.000
FWH3A	1.004	1.006	1.003	1.005	1.002	1.005
FWH3B	1.000	1.000	1.000	1.000	1.000	1.000
FWH3C	1.000	1.000	1.000	1.000	1.000	1.000
FWH5A	1.000	1.000	1.000	1.000	1.000	1.000
FWH5B	1.000	1.000	1.000	1.000	1.000	1.000
FWH6A	1.000	1.000	1.000	1.000	1.000	1.000
FWH6B	1.000	1.000	1.000	1.000	1.000	1.000
FWH7A	1.000	1.000	1.000	1.000	1.000	1.000
FWH7A	1.000	1.000	1.000	1.000	1.000	1.000
FWH1A	1.000	1.000	1.000	1.000	1.000	1.000
FWH1B	1.000	1.000	1.000	1.000	1.000	1.000
FWH1C	1.000	1.000	1.000	1.000	1.000	1.000
FWH2A	1.000	1.000	1.000	1.000	1.000	1.000
FWH2B	1.000	1.000	1.000	1.000	1.000	1.000
FWH2C	1.000	1.000	1.000	1.000	1.000	1.000
FWH3A	1.000	1.000	1.000	1.000	1.000	1.000
FWH3B	1.000	1.000	1.000	1.000	1.000	1.000
FWH3C	1.000	1.000	1.000	1.000	1.000	1.000
FWH5A	1.202	1.133	0.985	1.211	0.978	1.059
FWH5B	1.000	1.000	1.000	1.000	1.000	1.000
FWH6A	1.018	1.027	1.016	1.000	1.014	1.012
FWH6B	1.000	1.000	1.000	1.000	1.000	1.000
FWH7A	1.003	1.008	1.003	1.000	1.002	1.005
FWH7A	1.000	1.000	1.000	1.000	1.000	1.000

All values are normalized by a design condition.

so the operating conditions resulting from the thermal efficiency degradation of a component can affect the performance indices of neighboring components. Table 1 shows such effects, which are superficial rather than intrinsic. The simulation model producing Table 1 will be described in the next section in detail.

The upper table shows the results when the heat transfer area of train A of the first low pressure FWH, designated FWH1A, decreases by 10%; the lower table provides results when the heat transfer area of train A of the first high pressure FWH, designated FWH5A, decreases by 10%. Since FWHs are separated by independent trains, performance degradation of a FWH does not propagate over the trains. Since the deaerator fills the role of a buffer absorbing the impact of a malfunction of a FWH which can be located at either the up-stream or down-stream side, the change of performance indices over the deaerator seems negligible. The FWHs located down-stream, however, result in index variations due to the performance degradation of up-stream FWHs, even though they do not experience any problems. It seems reasonable for performance variation to taper off as feedwater flows down-stream. It can also be expected that the performance variation must be extremely complicated as multiple FWHs are under degradation. We believe that the performance variation shows the abnormality of a component, so that we are likely to make a mistake in determining maintenance schedules. One of the pre-requisites to evaluate the performance of FWHs should be, therefore, to distinguish intrinsic performance degradation from superficial observations. Such a pre-requisite should also be employed for all of the other components in turbine cycles (Heo, 2005).

2.2. Internal leakages of FWHs

Internal leakage is regarded as flow escape through the isolated path but still remaining inside the system boundary. Generally, the mixing of leaked feedwater with the steam induced thermal performance degradation. A more serious case is a tube leak in a high pressure FWH (HP FWH) producing a high-speed water jet that can cause damage to whatever happens to be in its path. Kidwell and June (2002) pointed out that this kind of tube leak should be caught early, so that there is time to deliberate and make a reasoned response. When an internal leakage happens, it costs utility money. Internal leakages impact plant efficiency and affect the ability to operate at full capacity. There are also direct costs associated with the appropriate repairs.

Primarily, tube-side failure occurs because of design or manufacturing defects, operational thermal stresses, or aging. We need to examine the following four cases of tube-side failure on which the related surveys have focused (Handen, Godwin, Wood, & Turner, 1996; Karg, Henderson, & Svensen, 1996):

- Pass partition plate leakage due to gradual erosion, which is not easily observed in tests.
- Inlet side tube-sheet leakage caused by bad welding at the tube and tube-sheet interface.
- Tube crack at U-section resulting from improperly formed tube bends, mechanical wear during thermal cycling, or stress corrosion.
- Outlet side tube-sheet leakage caused by bad welding at the tube and tube-sheet interface.

Fig. 2 shows the four leakage locations typically observed in FWHs. Thermal performance degradation resulting from internal leakages is observed using performance indices such as tube-side

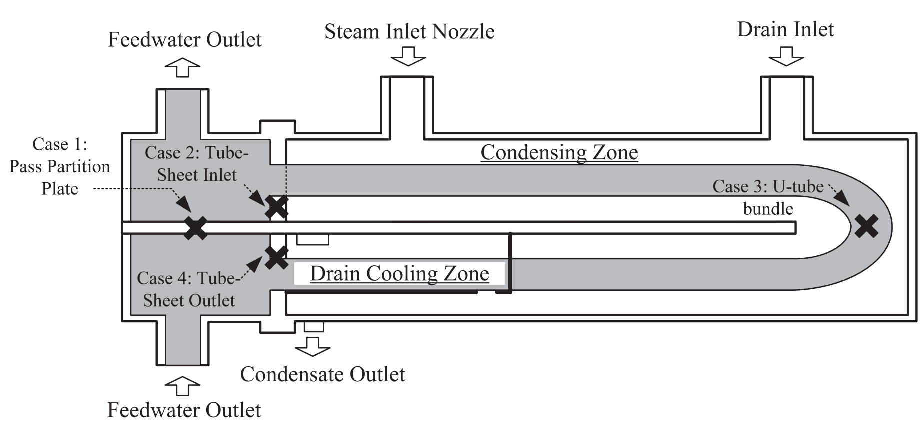

Fig. 2. Inside structure of a FWH and leakage locations.

DP, TD, TTD, and DCA as well as an electric output and/or heat rate. As opposed to external leakages such as valve stem leaks, it is impossible to directly detect internal leakage during normal operation. Indirect measurement techniques for detecting internal leakage have been proposed, such as a leakage tracking method using radioactive sources or a recirculation method, but they should be performed during a plant shutdown. While methods based on mathematical models and monitoring the performance indices of FWHs have been proposed by Shapiro (1986), Loparo, Buchner, and Vasudeva (1991), Handen et al. (1996), Reaedon, Muldoon, and April (1998), and Fantoni (2005), they lacked serious consideration of intrinsic and superficial performance degradation. Some of the methods based on analytical models exhibited difficulty in simultaneously achieving the quantification and the location detection of leakages.

3. Development of state estimation model

In order to propose a new solution while taking previous studies into account, we attempted to develop a neural network model which can distinguish between intrinsic and superficial performance degradation and achieve the functional requirements for detecting internal leakage. The overall framework of the solution, illustrated in Fig. 3, follows the development strategy of conventional CBM suggested by Hashemian (1995) and International Atomic Energy Agency (IAEA) (2007).

To detect anomalies such as a leakage, we need a set of signals provided in various leakage conditions and a mathematical model determining the location and the quantity of leakages using the given set. We will use the signal set – including flowrate, pressure, temperature, and electric output – which is generated by a turbine cycle simulation tool. The mathematical model is developed by a neural network. This series of processes is called 'the development of state estimation model' or simply 'training', and is the scope of this chapter. This could be considered a non-linear regression in terms of a mathematical viewpoint. For practical use, a set of signals in an arbitrary operating condition is the input to the state estimation model. The model compares the input set with the trained signal sets, and estimates the location and the quantity of a leakage. This process is named as to be 'state monitoring'.

3.1. Turbine cycle modeling and simulation

The neural network proposed in this study is regarded as the state estimation model providing expected performance indices under a current operating condition. To secure the data for training the neural network, we needed to develop the simulation model of a turbine cycle because it was unlikely to acquire the field data under various types of FWH leakage conditions. Since the state estimation model for detecting internal leakage in FWHs should be developed using the data acquired from well-controlled conditions, we decided to use a simulation model instead of using the data acquired from a power plant. The PEPSE (Performance Evaluation of Power System Efficiencies) that we chose for modeling the turbine cycle of the Korean nuclear power plant, OPR-1000 is a generic-purpose simulation toolbox for steam or gas turbine cycles (Alder, Blakeley, Fleming, Kettenacker, & Minner, 1996). Fig. 4 shows the turbine cycle model developed by PEPSE. The configuration of the model is based on the simplified piping & instrumentation diagram of the turbine cycle of OPR-1000 shown in Fig. 1. We call this model a 'base model' in this study. The base model starts at the outlet of a SG and ends at the inlet of the SG. It contains the entire piping network including a main steam system, a condensation system, and a main feedwater system, which are the essential systems for analyzing the effect of internal leakages. The accuracy of the base model was validated by comparing the results produced by the base model with the design heat balance diagrams for valve wide open (VWO), 100%, and 75% electric output which were provided by the turbine vendor.

In order to increase the flexibility of modeling the leaking positions and flowrate, we split the default FWH model provided by PEPSE into two sub-models: a condensing part and a drain cooling part. We corrected some internal parameters of the split FWHs so that they can produce the same design performance indices as those of the base model: for example, TTD, DCA, and pressure drop of tube- and shell-side. As a result, the box area in Fig. 4 is equivalently re-modeled to the box area in Fig. 5, which provides the same performance indices as that of Fig. 4.

We then simulated four internal leakage cases using the detailed FWH model. In each case, the leakage rate was set as 0.0–0.1% of a throttle flowrate. Figs. 6–9 show the results. All values in the figures are percent gain or loss. The vertical axis represents the normalized value, which equals 1.00 under normal operation without any leakage. The horizontal axis represents the leakage rate through a leak point, which is the percentage of the flowrate in tube-side.

The overall trend of performance indices under different leakage conditions looks somewhat correlated, but is not easily explained. For Case 1, TTD has a unique behavior, so it can be an important parameter to recognize the leakage around pass partition plates excluding the chances of Cases 2, 3, or 4. Cases 2–4

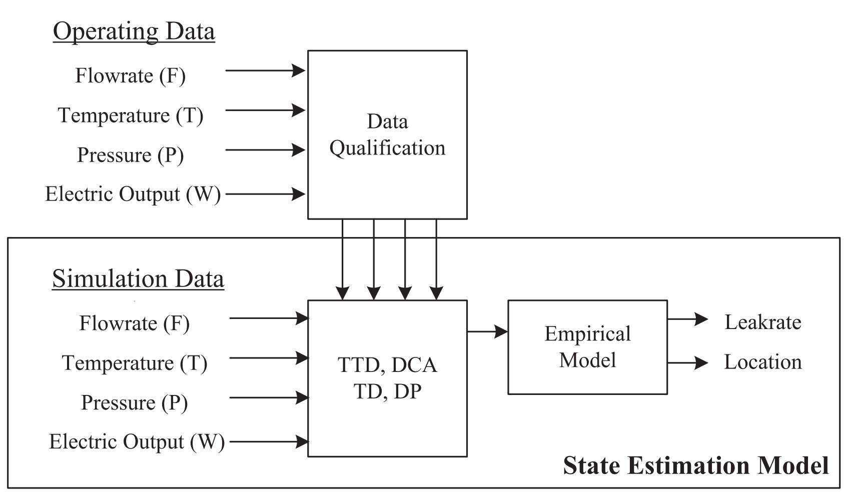

Fig. 3. Overall framework of internal leakage monitoring.

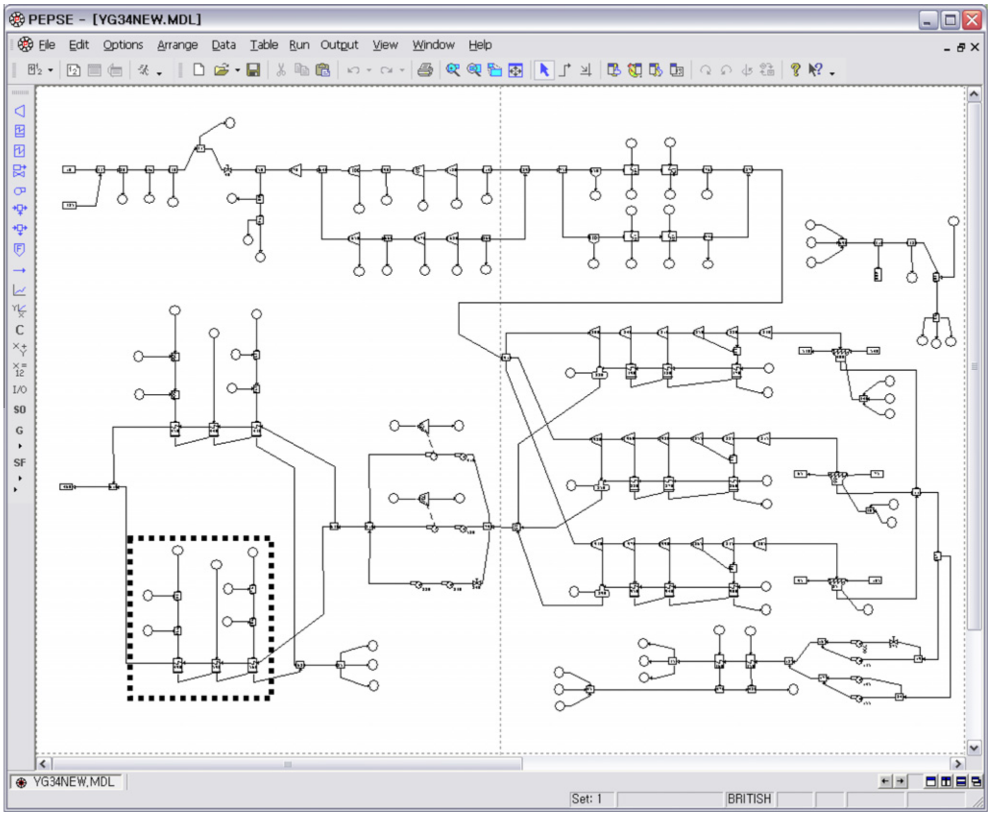

Fig. 4. Turbine cycle model of OPR1000 created by PEPSE.

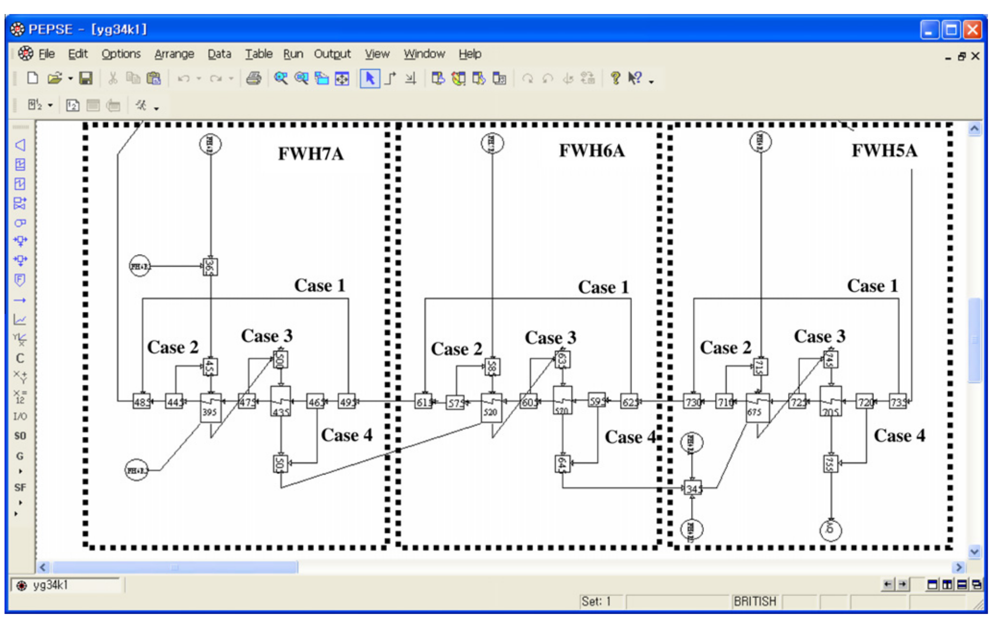

Fig. 5. Detailed model of the FWH train (equivalent to the box of Fig. 3).

show a certain trend, even though the performance indices in these cases look quite different from one another. First of all, the trend of tube-side TDs and TTDs is not noticeable because they have similar effects under all of the leakage conditions. The shell-side TDs and DCAs are apparently being changed. Their variation is related to the enthalpy of the leakage flow and the extracted steam from turbines. The combination of the enthalpy from both sides is dependent on the correlation between leakage flowrate and temperature. Since the total enthalpy of high leakage flowrate with a low temperature and low leakage flowrate with a high temperature are the same, the parametric trend of the shell-side TD and DCA in Cases 2–4 is complex. In terms of electric output and heat rate, the parametric trend was identical. The output of Case 1 decreases less than the output of the other cases. The cause of decreasing electric output is somewhat different: for Case 1, since the low temperature flow is bypassed to SGs, the heat load of the

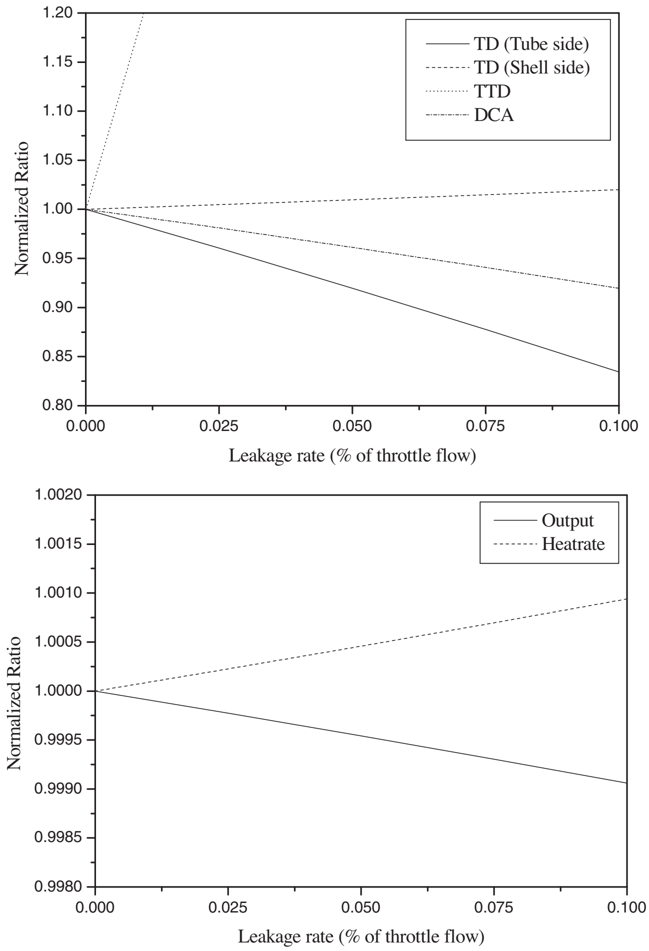

Fig. 6. Performance indices for Case 1, leakage at pass partition plate of FWH7A.

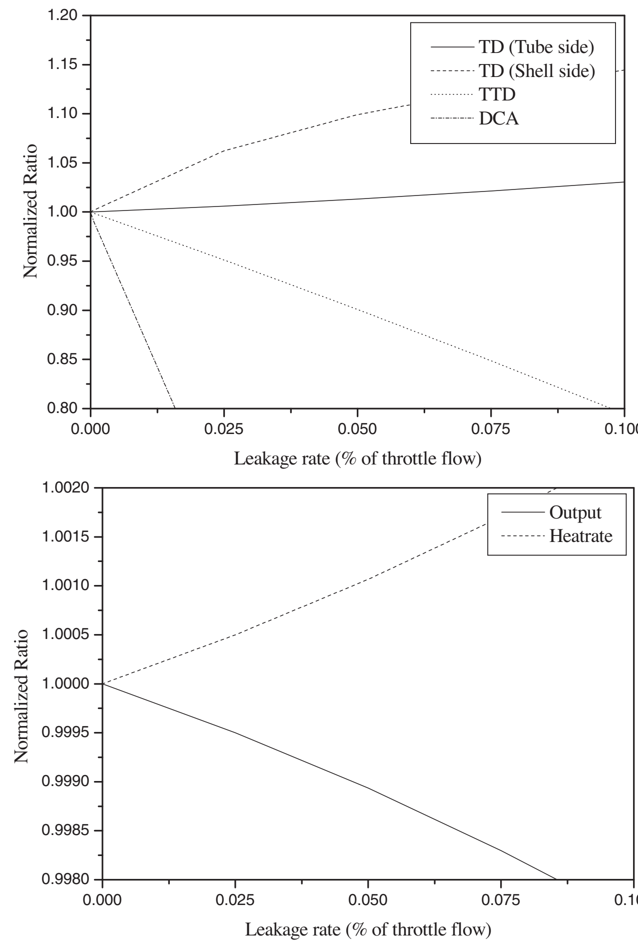

Fig. 7. Performance indices for Case 2, leakage at inlet tube-sheet of FWH7A.

SGs increases and the quality of the main steam decreases. For other cases, the leak flow results in the variation of turbine extraction flow.

In conclusion, we were able to observe a linear correlation between output (or heat rate) and leakage rate, as well as some characteristics of each case. These facts will be helpful to identify or diagnose internal leakages.

3.2. Development of neural network models

The neural network is a nonlinear regression technique that can be used to model complex relationships between inputs and outputs. Neural networks were originally mathematical models used to simulate biological neural networks, so they consist of interconnected groups of neurons, called nodes or perceptrons, and process information using a connectionist. The most important characteristic of neural networks may be their parallel computing capability, which is particularly useful when dealing with problems such as pattern classification, pattern completion, or function approximation that a conventional sequential algorithm cannot solve. It is notable that a neural network can be used as an arbitrary function approximation mechanism which learns from the observed data. The fundamentals of neural networks are widely known in CBM, and a lot of applications have been studied, so this paper will only provide a brief overview of the background theory.

Mathematically, the modeling of neural networks is done to find an approximation function, $f(x)$, which is defined as a composition of other functions, $g_j(x)$, which can further be defined as the composition of other functions or input variables in Eqs. (1) and (2):

$$f(\mathbf{x}) = K'\left(\sum_j w'_j g_j(\mathbf{x})\right), \tag{1}$$

$$g_j(\mathbf{x}) = K\left(\sum_i w_{ij} x_i\right), \tag{2}$$

where K and K' are predefined functions such as a logistic function or a hyperbolic tangent function, and w_{ij} is the weight given to the arrow between two nodes.

The goal of modeling neural networks is to find the coefficients vector, $\boldsymbol{w}$, which is termed ‘learning’ or ‘training’. Generally, updating the value of $\boldsymbol{w}$ is regarded as ‘learning,’ but sometimes changing the structure of a network itself can be called ‘learning’ in a specific neural network. There are numerous algorithms available for training a neural network. Most of these algorithms can be viewed as straightforward applications of optimization theories and statistical estimations, so a gradient descent method should be used to minimize the errors between the expected output sets and the calculated sets. If the learning algorithm and the scheme for minimizing errors are selected appropriately, the results of the neural network will be robust, in contrast with general regression models.

In order to develop the neural network model for estimating the leakage rate and position, a feed-forward neural network with a single hidden layer was used. As the nodes in the input layer,

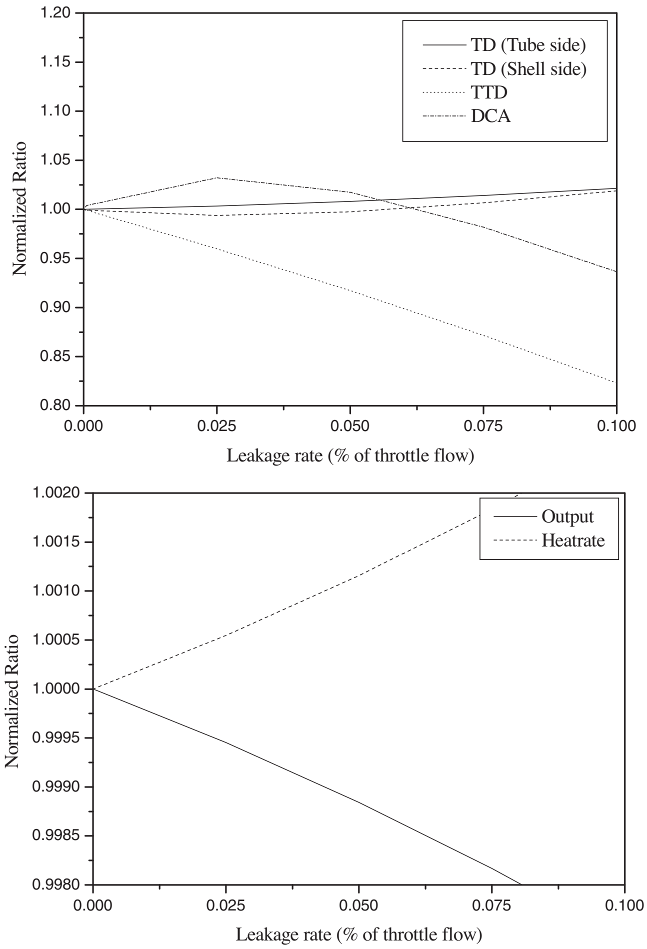

Fig. 8. Performance indices for Case 3, leakage at U tube section of FWH7A.

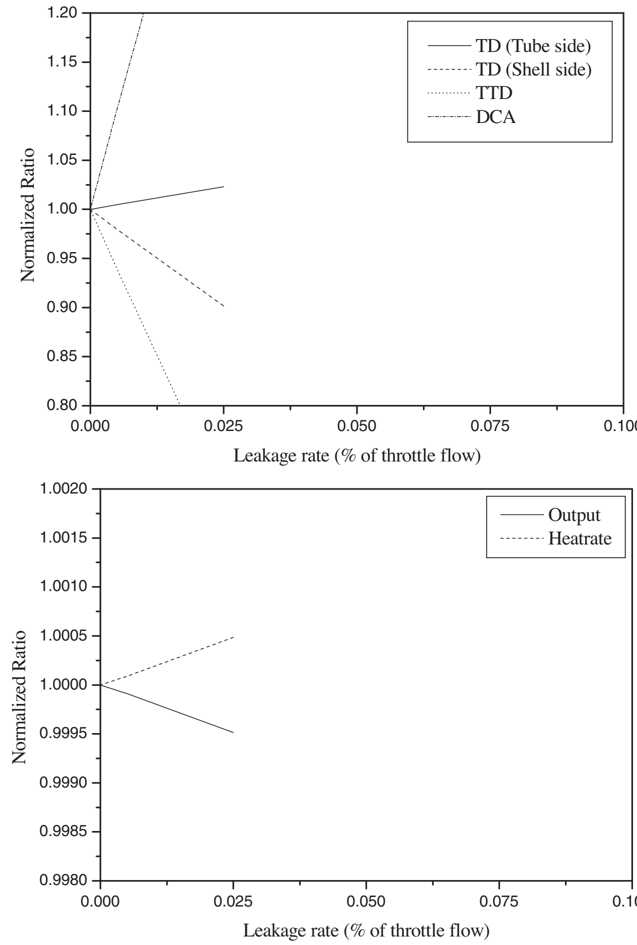

Fig. 9. Performance indices for Case 4, leakage at outlet tube-sheet of FWH7A.

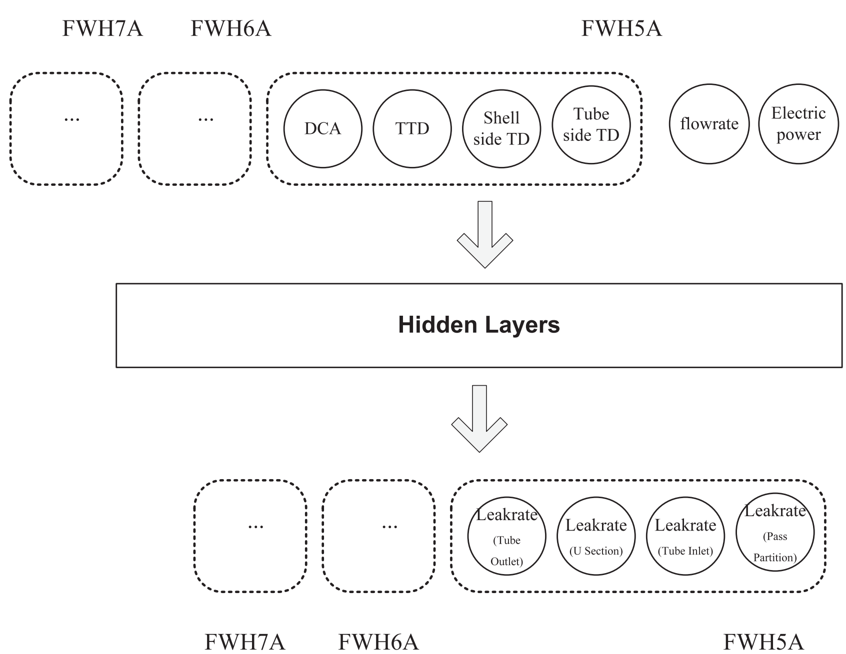

Fig. 10. Neural network structure for estimating internal leakages.

TTD, DCA, shell-side TD, and tube-side TD of FWHs 5A, 6A, and 7A were selected. In addition, electric power and feedwater flowrate was appended. In this model, four technical aspects were assumed: (1) The internal leakages take place in HP FWHs because the tube-side pressure is much higher than that of low pressure FWHs (LP FWHs). (2) Multiple leakages in a single train do not take place.

Table 2
Training data matrix.

Leak position	Leakage rate					
	FWH5A (%)		FWH6A (%)		FWH7A (%)	
Case 1 (pass partition plate)	10.00	7.50	10.00	7.50	10.00	7.50
	5.00	2.50	5.00	2.50	5.00	2.50
	0.05		0.05		0.05	
Case 2 (tube-sheet inlet)	10.00	7.50	10.00	7.50	10.00	7.50
	5.00	2.50	5.00	2.50	5.00	2.50
	0.05		0.05		0.05	
Case 3 (U tube section)	10.00	7.50	10.00	7.50	10.00	7.50
	5.00	2.50	5.00	2.50	5.00	2.50
	0.05		0.05		0.05	
Case 4 (tube-sheet outlet)	5.00	2.50	5.00	2.50	5.00	2.50
	0.05					

Once a failure occurs, we are able to detect it before any proceeding failures occur. (3) The effect of internal leakages does not propagate over the trains or the deaerator, which was demonstrated in Table 1. (4) There is no other performance degradation mechanism except leakages. Presumably performance degradation inside a FWH should affect the variation of performance indices. In this modeling, those affects were excluded to simplify the problem for the time being.

On the basis of these assumptions, a total of 14 nodes were prepared in the input layer of the suggested neural network. In the output layer, four nodes were used per a single FWH. Each node represents a leakage rate at a specific location. For example, the output node encoded by $[\gamma, 0, 0, 0]$ stands for γ % of the leakage rate at the pass partition plate. The second number is the leakage rate at the inlet of a tube side. The third number is the leakage rate at the U section, while the final number is the leakage rate at the outlet of a tube side. Since there are three FWHs, the total number of nodes at the outlet layer is 12 (=4×3). Fig. 10 depicts the structure of the neural network for estimating the leakage rate and position of FWHs.

Two hidden layers were involved in building the neural network. The number of nodes in each layer is 23 and 19, respectively. The training data is provided in Table 2 in a matrix form. The leakage rate in Table 2 represents the percentage of the flowrate in tube-side.

3.3. Validation results

The data sets in Section 3.2 were involved in the training of the neural network, and some more simulation results were additionally acquired for testing processes. The results of the training are as follows. Table 3 shows the test results for FWH7A using the training data sets after reducing the training error by the order of 10^{-7}. It is expected that the estimation capability of the neural network should be nearly perfect as well. To see the capability of the state estimation model for practical use, additional validations were performed. Table 4 shows the test results using the additional simulation data sets, which are different from the sets used for training the neural network. We conducted two tests, particularly focusing on an upstream FWH5A and a downstream FWH7A to see their different impact on the performance indices of the neighbor FWHs.

Since the leakages taking place in FWH7A do not have a serious effect on FWH5A or 6A, the estimation results show only less than 0.5% of errors in terms of absolute value. Even though the leakages taking place in the FWH5A distorted the performance indices of FWH6A and 7A, the state estimation model could estimate the leak points and amount within 1.0% of the error bounds. From the results, it is expected that the state estimation model can be applied to each train individually in the same manner, for example, to train B of HP FWHs or to train C of LP FWHs. Even though the model was satisfactory under the simulated conditions, we still need more validations using experimental data. Furthermore, it should be noted that the proposed model needs to be improved particularly under the situation that we assumed.

4. Conclusions

The ultimate purpose of the diagnosis may be the economical operation and maintenance of power plants. One of the currently highlighted trends among diagnosis methodologies should be the CBM which is based on advanced information technologies.

This study was performed to suggest another application based on the framework of the CBM. The study attempted to suggest a means of detecting, during normal operation, an internal leakage occurring in FWHs. One of the most significant factors to affect the capability of the CBM should be the state estimation model. While this study improved the accuracy and coverage of the state

Table 3
Test results for FWH7A using the training data sets (Observation: simulation results, Estimation: neural network results).

Leak rate	Location											
	Pass partition plate			Tube-sheet inlet			U-tube section			Tube-sheet outlet		
	Observation	Estimation	Abs. error (%)	Observation	Estimation	Abs. error	Observation	Estimation	Abs. error	Observation	Estimation	Abs. error
Case 1	**1.0000**	**1.0000**	0.000	0.0000	0.0000	−0.003	0.0000	0.0000	0.000	0.0000	0.0001	−0.009
	0.7500	**0.7500**	0.000	0.0000	−0.0001	0.008	0.0000	−0.0000	0.001	0.0000	−0.0001	0.005
	0.5000	**0.5000**	−0.001	0.0000	0.0001	−0.011	0.0000	−0.0001	0.006	0.0000	−0.0000	0.001
	0.2500	**0.2500**	0.000	0.0000	−0.0001	0.009	0.0000	0.0001	−0.010	0.0000	−0.0002	0.020
	0.0050	**0.0052**	−0.020	0.0000	0.0001	−0.009	0.0000	−0.0006	0.064	0.0000	−0.0000	0.003
Case 2	0.0000	0.0000	−0.003	**1.0000**	**0.9999**	0.009	0.0000	−0.0001	0.008	0.0000	−0.0001	0.010
	0.0000	−0.0001	0.008	**0.7500**	**0.7503**	−0.026	0.0000	0.0002	−0.023	0.0000	0.0001	−0.006
	0.0000	0.0001	−0.011	**0.5000**	**0.4997**	0.034	0.0000	−0.0002	0.024	0.0000	0.0003	−0.028
	0.0000	−0.0001	0.005	**0.2500**	**0.2502**	−0.023	0.0000	0.0001	−0.010	0.0000	−0.0003	0.032
	0.0000	−0.0009	0.085	**0.0050**	**0.0034**	0.158	0.0000	0.0021	−0.208	0.0000	−0.0001	0.011
Case 3	0.0000	0.0000	−0.003	0.0000	0.0001	−0.014	**1.0000**	**1.0001**	−0.010	0.0000	0.0002	−0.015
	0.0000	−0.0000	0.004	0.0000	−0.0004	0.038	**0.7500**	**0.7497**	0.033	0.0000	−0.0002	0.024
	0.0000	−0.0000	0.003	0.0000	0.0003	−0.027	**0.5000**	**0.5005**	−0.049	0.0000	−0.0002	0.016
	0.0000	0.0001	−0.011	0.0000	0.0001	−0.008	**0.2500**	**0.2496**	0.043	0.0000	0.0005	−0.045
	0.0000	0.0000	−0.001	0.0000	−0.0010	0.095	**0.0050**	**0.0054**	−0.038	0.0000	0.0002	−0.018
Case 4	0.0000	0.0000	−0.001	0.0000	0.0000	0.000	0.0000	−0.0000	0.001	**0.2500**	**0.2500**	0.000
	0.0000	−0.0001	0.007	0.0000	−0.0001	0.005	0.0000	0.0002	−0.021	**0.0050**	**0.0047**	0.027

Table 4
Test results using the test data sets (Upper: Leakage in FWH5A, Lower: Leakage in FWH7A).

Leak rate	Location											
	Pass partition plate			Tube-sheet inlet			U-tube section			Tube-sheet outlet		
	Observation	Estimation	Abs. error (%)	Observation	Estimation	Abs. error	Observation	Estimation	Abs. error	Observation	Estimation	Abs. error
FWH 5A	**0.7000**	**0.6950**	0.500	0.0010	0.0000	0.100	−0.0020	0.0000	−0.199	0.0000	0.0000	0.000
	0.0000	−0.0005	0.047	**0.2000**	**0.2020**	−0.200	0.0010	0.0000	0.100	0.0000	0.0000	0.000
	0.0000	0.0000	0.000	0.0000	−0.0001	0.008	**0.1000**	**0.1100**	−1.000	0.0000	−0.0009	0.090
	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0007	−0.070	**0.1000**	**0.0998**	0.020
FWH 6A	0.0000	0.0000	0.000	0.0000	0.0005	−0.047	0.0000	0.0000	−0.002	0.0000	0.0000	0.000
	0.0000	−0.0006	0.058	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000
	0.0000	0.0005	−0.053	0.0000	−0.0001	0.010	0.0000	0.0000	0.000	0.0000	−0.0002	0.018
	0.0000	0.0000	0.000	0.0000	0.0009	−0.091	0.0000	0.0004	−0.042	0.0000	0.0000	0.000
FWH 7A	0.0000	0.0000	0.000	0.0000	0.0010	−0.097	0.0000	0.0000	0.000	0.0000	0.0000	0.000
	0.0000	0.0003	−0.028	0.0000	0.0000	0.000	0.0000	0.0002	−0.017	0.0000	0.0002	−0.015
	0.0000	0.0004	−0.041	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000
	0.0000	0.0000	0.000	0.0000	0.0007	−0.070	0.0000	0.0000	0.000	0.0000	0.0000	0.000
FWH 5A	0.0000	0.0000	0.000	0.0000	0.0010	−0.100	0.0000	0.0010	−0.100	0.0000	0.0000	0.000
	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0010	−0.100	0.0000	0.0000	0.000
	0.0000	0.0020	−0.200	0.0000	−0.0010	0.100	0.0000	−0.0010	0.100	0.0000	0.0010	−0.100
	0.0000	0.0000	0.000	0.0000	0.0030	−0.300	0.0000	0.0000	0.000	0.0000	0.0000	0.000
FWH 6A	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000
	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000
	0.0000	0.0000	0.000	0.0000	−0.0010	0.100	0.0000	−0.0010	0.100	0.0000	0.0000	0.000
	0.0000	0.0010	−0.100	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000
FWH 7A	**0.3000**	**0.2970**	0.300	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	−0.0010	0.100
	0.0000	0.0000	0.000	**0.2000**	**0.2000**	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000
	0.0000	0.0010	−0.100	0.0000	0.0000	0.000	**0.6500**	**0.6490**	0.100	0.0000	0.0000	0.000
	0.0000	0.0000	0.000	0.0000	0.0010	−0.100	0.0000	0.0000	0.000	**0.2000**	**0.1990**	0.100

estimation model using the physical model referred as turbine cycle simulation, the correlation between causes and consequences from the physical model was modeled by a neural network.

The neural network for the state estimation model was implemented to distinguish the location and the flowrate of internal leakages of FWHs. To secure the appropriate data sets for the study, detailed modeling of FWHs covering the leakage from tubes, tube-sheets, or pass partition plates using PEPSE was carried out. Since the operational characteristics of FWHs are coupled with one another and/or with other neighbor components such as turbines, the recognition of internal leakages is difficult with only an analytical model and the information of pressure and temperature observed at the inlet and outlet of tube- and shell-side. We proposed a neural network-based correlation model that successfully detected the position of internal leakages and quantified the amount of rates within an acceptable error bound. It is expected that the neural network model can be applied to other trains and/or power plants of FWHs in the same manner.

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