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Classification of Feedwater Heater Performance Degradation Using Residual Sign Matrix

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1. Introduction

Since a performance of Feedwater Heater (FWH) is directly related to the thermodynamic efficiency of Nuclear Power Plants (NPPs), performance degradation of FWH results in loss of thermal power and ultimately business benefit. Nevertheless, it is difficult to diagnose its degradation of performance during normal operation due to its minor changes in process parameters, for instance, pressure, temperature, and flowrate.

In this paper, six degradation modes have been analyzed and the performance indices for FWH such as Terminal Temperature Difference (TTD) and Drain Cooling Approach (DCA) have been used to diagnose degradation modes. The Residual Sign Matrix (RSM) has been used to obtain the tendency of the variations of performance indicators and Support Vector Classification (SVC), which is widely used for regression or classification of data, has been performed to classify the degradation mode of FWH.

PEPSE (Performance Evaluation of Power System Efficiencies) simulation [1], which is a plant simulation software simulating plant static characteristic and building energy balance model, has been used to generate the data of performance indices of FWH and actual measurements of FWH from NPPs was used to validate the classification model.

2. Methods and Results

This section describes the algorithm of the classification model for FWH degradation and the verification result using field data.

2.1 Performance Indices of Feedwater Heater

The FWH is a heat exchanger that preheats water delivered to a steam generator using steam extracted from the steam turbine to improve thermodynamic efficiency of the turbine cycle and reduce the irreversibility involved in steam generator. Figure 1 shows the configuration of feedwater heater in NPP [2].

In this paper, low pressure feedwater heaters were used for simulation. 8 performance indices were selected among state variables obtained from the PEPSE simulation of the representative 6 degradation of FWH (High drain level, Low shell pressure, Tube plugging, Tube fouling, Pass partition plate leakage, Tube leakage). Then, they were used to determine 6 degradation modes.

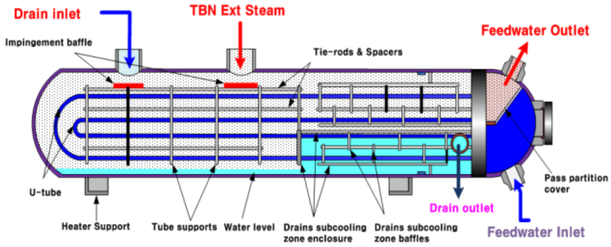

Fig. 1. Schematic diagram of Feedwater Heater (2-zone, Shell-Tube type) in NPP

TTD is determined by the difference between saturated temperature at shell inlet pressure and tube outlet temperature, and DCA is calculated as the temperature difference between shell outlet and tube inlet. Equation (1) and (2) shows the descriptions of TTD and DCA, respectively [3].

$$\mathrm{TTD} = \mathrm{T}_{SAT\_shell\_I} - \mathrm{T}_{tube\_O} \quad (1)$$
$$\mathrm{DCA} = \mathrm{T}_{shell\_O} - \mathrm{T}_{tube\_I} \quad (2)$$

In addition, temperature difference between tube inlet and outlet and temperature difference between shell inlet and outlet are selected as additional indices. Each temperature difference can be calculated as follows.

$$\Delta\mathrm{T}_{tube} = \mathrm{T}_{tube\_O} - \mathrm{T}_{tube\_I} \quad (3)$$
$$\Delta\mathrm{T}_{shell} = \mathrm{T}_{shell\_O} - \mathrm{T}_{shell\_I} \quad (4)$$

Finally, tube inlet/outlet temperature and shell inlet/outlet temperature are used as it is.

The temperature differences between inlet and outlet of FWH such as equation (1) to (4) indicate performance change of FWH itself, and FWH inlet or Outlet temperature each represents the effects resulted from the degradation.

2.2 Development of the Classification Model

2.2.1 Residual Sign Matrix (RSM)

Through the 6 performance degradation data obtained by simulations, it can be seen that the 8 performance indices fluctuate with degradation. In order to diagnose degradation using the trend of variation of measurement, there is a need of simple effective trend identifiers because real measured values are noisy. Using RSM, it is possible to obtain appropriate information of the variables in noise environment.

Table 1: RSM for Simulated Degradation

	TTD	DCA	ΔT_{tube}	T_{tube_I}	T_{tube_O}	ΔT_{shell}	T_{shell_I}	$\mathbf{T_{shell\_O}}$
High Drain Level	1	-1	-1	1	-1	1	1	-1
Low Shell Pressure	-1	-1	-1	1	-1	-1	-1	-1
Tube Plugging	1	1	-1	1	-1	-1	1	1
Tube Fouling	1	1	-1	1	-1	-1	-1	1
Pass Partition Plate Leakage	1	-1	-1	1	-1	1	1	1
Tube Leakage	1	-1	-1	1	-1	1	1	-1

Table 2: SVC Results using simulation data set

	High Drain Level	Low Shell Pressure	Tube Plugging	Tube Fouling	Pass Partition Plate Leakage	Tube Leakage
[Pred.] High Drain Level	6 (100.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	1 (16.67%)
[Pred.] Low Shell Pressure	0 (0.00%)	2 (100.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
[Pred.] Tube Plugging	0 (0.00%)	0 (0.00%)	9 (100.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
[Pred.] Tube Fouling	0 (0.00%)	0 (0.00%)	0 (0.00%)	4 (100.00%)	0 (0.00%)	0 (0.00%)
[Pred.] Pass Partition Plate Leakage	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	5 (100.00%)	0 (0.00%)
[Pred.] Tube Leakage	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	5 (83.33%)

Accuracy: 96.88%

In this paper, the RSM was proposed as a trend identifier of variables. The RSM is represented the difference between the measured value relative to the normal condition value as a simple signed signal. The difference between the normal value and the measured value is called *Residual* and can be calculated as follows.

$$Residual(i) = X_i - X_N \tag{5}$$

where X_N is normal value and X_i is measured value.

The measurement in RSM can simply express the trend of variation of the variables. RSM can be made as follows:

$$\text{if } \begin{cases} Residual(i) > 0, & RSM(i) = +1 \\ Residual(i) = 0, & RSM(i) = \ \ 0 \\ Residual(i) < 0, & RSM(i) = -1 \end{cases} \tag{6}$$

Table 1 represents RSM related 8 performance indices, which is built from the result of above mentioned 6 FWH degradation modes simulated by PEPSE.

2.2.2. SVC Model

In this study, SVC was used to classify the degradation modes of FWH. RapidMiner [4], data mining software was used to build the SVC model.

SVC [5] can classify data by using the Optimal Separating Hyperplane (OSH) at a high dimension. As shown in Figure 2, the case of the data that cannot be separated linearly, SVC performs non-linear mapping using the kernel trick.

There are polynomial, RBF (Radial Basis Function), and sigmoid function for SVC kernel function. In this paper, RBF kernel was used. Equation 7 shows the RBF kernel function.

$$K(X_i, X_j) = e^{-\frac{\|X_i - X_j\|^2}{2\sigma^2}} \tag{7}$$

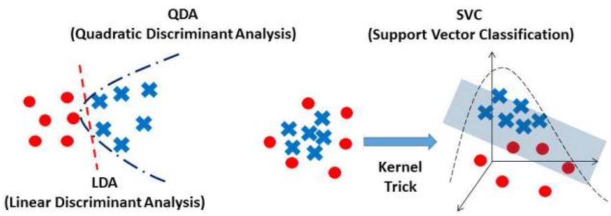

Fig. 2. Nonlinear mapping using kernel Trick, which transforms the data into a higher dimension

2.2.3. Classification Model Validation

The RSM was used as the training data to build the SVC model. The RSM data were divided into two sets, training and test sets for algorithm validation of the model. 70% of the data were used for training set, and the other 30% were test data set. First, the SVC model was built using the training data set, and then the test data set was used to check its predictive capability. Then, the final SVC model was made with whole data.

As a result of classification, the performance of the model is evaluated. The representative measurement of the performance of the model is Accuracy. The accuracy is defined as the number of correct predictions (classification) made to the total number of predictions (classification) made. It is determined as below.

$$Accuracy = \frac{The\ number\ of\ correct\ predictions}{The\ number\ of\ total\ predections} \tag{8}$$

Table 3: RSM for field degradation data

	TTD	DCA	ΔT_{tube}	T_{tube_I}	T_{tube_O}	ΔT_{shell}	T_{shell_I}	$\mathbf{T_{shell\_O}}$
Tube Plugging (Example 1)	1	1	-1	-1	-1	-1	-1	1
Tube Plugging (Example 2)	1	1	-1	-1	-1	-1	-1	1
Tube Leakage (Example 3)	1	-1	-1	-1	-1	1	1	-1
Tube Leakage (Example 4)	1	-1	-1	-1	-1	1	1	-1

Table 2 shows the classification result of the test set. In Table 2, the first heading is a real degradation mode of test data and the first column represents the predicted degradation mode. Each cross shows the number and proportion of the predictions. The accuracy of the model is also placed at the bottom of the Table 2.

2.3 Verification of Classification Model using Field Data

To check the possibility of practical application, the verification using field data is required. We conducted verification of the model using practical examples. Here, four examples of tube plugging and tube leakage were used. Table 3 shows the field data in RSM investigated by virtue of utility's co-operation.

Using the classification model created in Section 2.2, the performance degradation modes of the field data were predicted. Table 4 shows prediction rank of the field data. As a result, four examples were predicted correctly with the highest probability.

Table 4: Prediction rank of the field data

	First	Second	Third
Tube Plugging 1	Tube Plugging	Tube Fouling	Tube Leakage
Tube Plugging 2	Tube Plugging	Tube Fouling	Tube Leakage
Tube Leakage 1	Tube Leakage	High Drain Level	Tube Plugging
Tube Leakage 2	Tube Leakage	High Drain Level	Tube Plugging

2.4 Performance indices of FWH under various tube leakage conditions

The tube leakage data for training are obtained from specific leakage condition of a specific LP FWH of a NPP. This section particularly focuses on performance indices of FWH under various leakage conditions. To identify the change of performance indices of FWH under various leakage condition, detailed simulation was conducted according to location of tube leakage. Simulation was carried out on 6 cases of HP/LP feedwater heater as follows:

- Case 1: Feedwater is leaked at the tube inlet side and drained to the shell inlet side.
- Case 2: Feedwater is leaked at the tube inlet side and drained to the shell outlet side.
- Case 3: Feedwater is leaked at the tube outlet side and drained to the shell inlet side.
- Case 4: Feedwater is leaked at the tube outlet side and drained to the shell outlet side.
- Case 5: Feedwater is leaked at the U-tube and drained to the shell inlet side
- Case 6: Feedwater is leaked at the U-tube and drained to the shell outlet side.

As a result, even if tube leakage occurs at the same location RSM have different patterns as leakage rate changes, and performance indices under various leakage conditions such showed different patterns.

3. Conclusions

In this paper, six degradation modes have been analyzed and the performance indices for FWH have been used to diagnose what degradation mode occurs. The RSM was proposed as a trend identifier of variables. Using RSM, it is possible to obtain appropriate information of the variables in noise environment since noise can be compressed while the original information is being converted to a trend. The SVC has been performed to classify the degradation mode of FWH, and then actual measurements of FWH from NPPs was used to validate the classification model.

Performance indices under various leakage conditions show different patterns. In further study, tube leakage simulations for the various cases will be needed. In addition, it is necessary to verify classification model using more actual degradation data.

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