Diagnosis Method for Thermal Efficiency Degradation in Turbine Cycle

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1. Introduction

According to the development of the IT technologies, the brisk activations to apply advanced IT technologies to power plants are now being researched in various ways. As one of the applications, thermal efficiency monitoring and diagnosis is a conventional but still pending issue.

Authors suggested an idea to diagnose the causes of degradation, particularly, in a turbine cycle since thermal efficiency is strongly dependent on the performance of a turbine cycle in nuclear power plants. The main idea is based on the algebraic model as an inference engine, which includes the correlation between the inputs for representing the cause of degradations and the simulation outputs representing the measured observations. This idea was proposed in an author's previous paper and it was improved such that the propose model can investigate more various and detailed causes [1].

2. Methods and Results

2.1 Assumptions

There are two assumptions, the superposition rule and the linearity hypothesis. Before an explanation for assumptions, following words should be defined;

1. ΔP_i^I : performance change caused by the intrinsic degradation in i^{th} component
2. ΔP_i^U : performance change caused by the induced degradation in i^{th} component
3. ΔP_i^S : the sum of ΔP_i^I and ΔP_i^U

2.1.1 Superposition of Performance Changes

Figure 1 and Equation (1) show that the superposition of performance changes as a schematic and mathematic way. From a practical viewpoint, it is impossible to distinguish between intrinsic degradations and induced degradations by observation.

$$\Delta P_i^S = \Delta P_i^I + \Delta P_i^U \qquad (1)$$

2.1.2 Linearity of Performance Changes

In Figure 2, P_i and P_j represents performance indices of a certain component. We hypothesized the effects of each other's performance index are proportional in a certain short range, that is a first order approximation described as Equation (2).

$$P_i = \beta_{ji} + w_{ji} P_j \qquad (2)$$

2.2 Idea

Equation (1) can be rearranged to Equation (3) by the linearity hypothesis conclusively.

$$\Delta P_i^S = \sum w_{ji} \Delta P_j^I \qquad (3)$$

Performance change of i^{th} component, ΔP_i^S represents the multiple combination of performance indices of j^{th} component, ΔP_j^I and the regression coefficient affecting from j^{th} component to i^{th} component, w_{ji} .In Equation (3), ΔP_i^S comes from the result of thermal performance analysis using plant signals and the regression coefficient w_{ji} can be calculated by sensitivity analysis using a simulation model. If the number of components is *N*, Equation (3) can be expanded to equation (4). In Equation (4), the only unknown is ΔP_i^I, which is vector of performance changes representing intrinsic components degradation or boundary condition changes. The other parameters, such as ΔP_i^S and w_{ji} , can be obtained by sensors and simulation results.

$$\begin{bmatrix} \Delta P_1^S \\ \Delta P_2^S \\ . \\ . \\ \Delta P_N^S \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & . & . & w_{1N} \\ w_{21} & w_{22} & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ w_{N1} & . & . & . & w_{NN} \end{bmatrix} \times \begin{bmatrix} \Delta P_1^I \\ \Delta P_2^I \\ . \\ . \\ \Delta P_N^I \end{bmatrix} \qquad (4)$$

Therefore, of the intrinsic performance degradations can be determined by using Equation (4) when we have superficial performance data, ΔP_i^S and regression coefficient, w_{ji} as input data.

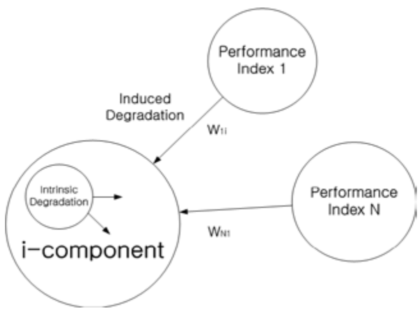

Fig.1 Relation between the performance indices

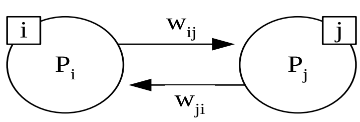

Fig.2 Mathematical model for the influence of component degradation

Table.1 Performance degradation diagnosis results

Simulated causes	Normalized superficial data, ΔP^S		Normalized intrinsic data, ΔP^I		Diagnosis results
Number of tube changes in FWH before the last	Power	-0.00004	Number of tube in FWH before the last	0.22869	Heat transfer area decrease
	Heat rate	-0.00021	Number of tube in the last FWH	0.00000	-
	TTD in the last FWH	0.00574	Condenser shell pressure	0.00000	-
	Main steam flow rate	0.00000	Main steam flow rate	0.00000	-
Number of tube changes in the last FWH	Power	-0.00186	Number of tube in FWH before the last	0.00000	
	Heat rate	0.00030	Number of tube in the last FWH	0.26437	Heat transfer area decrease
	TTD in the last FWH	0.64991	Condenser shell pressure	0.00000	-
	Main steam flow rate	0.00000	Main steam flow rate	0.00000	-
Condenser shell pressure changes	Power	0.02039	Number of tube in FWH before the last	0.00000	
	Heat rate	-0.02082	Number of tube in the last FWH	0.00000	
	TTD in the last FWH	0.00000	Condenser shell pressure	-0.77427	Condenser shell pressure increase
	Main steam flow rate	0.00000	Main steam flow rate	0.00000	-
Main steam flow rate changes	Power	0.00203	Number of tube in FWH before the last	0.00000	
	Heat rate	0.00003	Number of tube in the last FWH	0.00000	
	TTD in the last FWH	-0.00083	Condenser shell pressure	0.00000	
	Main steam flow rate	0.00263	Main steam flow rate	0.00263	Main steam flow rate decrease

Mathematically, regression coefficient w_{xy} defined in Equation (5), is performance variation, Δy per unit performance change factor, Δx .

$$w_{xy} = \frac{\Delta y}{\Delta x} = \frac{y_{ini} - y_{fin}}{x_{ini} - x_{fin}} \qquad (5)$$

Where x_{ini} , y_{ini} are the initial values of each parameters representing certain design value and x_{fin}, y_{fin} are the changed values of each parameter representing operation state value.

2.3 Validations

The validation of the proposed algorithm is handled through examples. All data for the validation were referred from one of the operating power plants in Korea. Table 1 shows the results of validation for this idea. Left two columns represent each root case cases and its data. Right two columns represent its diagnosis result and specific root causes. As table 1 show, this inference engine can find the root causes for each degradation state of turbine cycle.

3. Conclusions

In this paper, the thermal performance degradation diagnosis method based on turbine cycle simulation under abnormal conditions and a regression model has been introduced. The proposed method performs the diagnosis task by comparing actual plant data representing superficial performance indices with root cause data representing abnormal conditions of components and boundary conditions, using a regression model. The major focus was to find out root causes in a multiple degradation situation where not only component effects exist but also, boundary conditions change. From the results obtained in this study, we concluded this method could meet the requirements as an inference engine for thermal performance analysis and compensate the weaknesses of the previous model.

REFERENCES

[1] Gyunyoung Heo, Soon Heung Chang: Algebraic Approach for the Diagnosis of Turbine Cycles in Nuclear Power Plants, Nuclear Engineering and Design, June. 2005: 1457-1467.