Proceedings of the Korean Nuclear Society Spring Meeting
Gyeongju, Korea, 2004

Algebraic Model for Root-Cause Diagnosis in Nuclear Turbine Cycles

Gyunyoung Heo and Soon Heung Chang
Korea Advanced Institute of Science and Technology
Department of Nuclear and Quantum Engineering
373-1 Kuseong-dong, Yuseong-gu, Daejeon 305-701, Republic of Korea

Abstract

From considering practical needs, authors proposed a diagnosis model to identify the performance degradation of steam turbine cycles in nuclear power plants(NPPs). In this study, the diagnosis is limited to the component-level root cause analysis. That is, this diagnosis model answers which component is the main reason of degradation of electric output or heat rate. Authors knew there were few diagnosis applications in NPPs currently because of various technological, financial, political characteristics. So a great part of the diagnosis has been dependent on efficiency staff's experience and knowledge. However as economic competition becomes severe, the efficiency staff in plants is asking for practical diagnosis-supporting tools. The essential concept of the proposed diagnosis model is the superposition rule of degradation phenomena. Though the superposition rule is not so significant statistically, almost of the performance indices are fairly compatible with this model. Using the superficial degradation which is observable in performance tests, and the correlation matrix among the performance indices, the proposed model can find the intrinsic degradation that is the root cause of overall performance degradation. Authors developed a proto-type model of quantitative root-cause diagnosis and validated the background theory using the simulated data. The turbine cycle diagnosis-supporting tool using this model was applied to Gori NPP unit 3&4.

I. Introduction

Until these days the efficiency of nuclear power plants(NPPs) is being focused on nuclear reactor itself such as the optimization of safety margins, the improvement of nuclear fuel, or the enhancement of critical heat flux. However the concern about the efficiency of turbine cycle has been increased under deregulation environment. The reduction of operating cost seems to be the first target to compete other power plants or renewable energy sources in the future. Actually the concern about performance of turbine cycle in NPPs was not so high with comparing to that of fossil-fuel plants. This may be because of the difficult startup and shutdown, and continuously long operation interval. However a lot of activities to increase the performance of turbine cycle started under strong deregulation environment, and one of the representative examples is the application of ultrasonic flowmeter for the accurate measurement of main feedwater flowrate[1].

From considering this situation, authors tried to make a technical road-map for the long-term research planning for the enhancement of turbine cycle efficiency[2]. The technical road-map can be divided into three parts; sensor & data acquisition, analysis, and diagnosis. And according to this technical road-map, we suggested strategies and made a little progress in sensor & data acquisition part and analysis part[3~6]. However it is clear that the accurate and rapid identification for the root cause of electric loss plays the most important role after all. Authors have investigated the status of turbine cycle performance tests which have been carried out in Korean NPPs for a long time. Though the operation of turbine cycles was already standardized, the performance diagnosis to check functional degradation seems to be still a pending issue. Especially in case of NPPs which use saturated steam as working fluid, since it is not easy to identify fluid conditions such as enthalpy, entropy, or specific volume, even the observation of performance degradation is not clear. Therefore the suggestion of a reliable as well as an applicable diagnosis methodology is not so easy job.

As a degradation diagnosis method about complex energy system, thermoeconomic analysis is popular[7~9]. This method suggested the detail analysis procedures for energy as well as exergy flow of thermal systems such as a power plant or a chemical plant. The concept merging thermodynamic properties and actual cost made the cost-benefit evaluation possible. Also the study for malfunction effect which is based on intrinsic malfunction and induced malfunction was not only compatible but also beneficial to author's diagnosis road-map. However the link with current performance tests which are based on enthalpy concept was difficult because thermoeconomic analysis was focused on information about internal loss. It is not easy to accomplish the performance test, analysis, and diagnosis using just the Second law of thermodynamics in NPPs. Aside from thermoeconimic analysis, a lot of intelligent or heuristic diagnosis methods have been proposed. As the applications to turbine cycle in NPPs among the proposed methodologies, there are neural networks, genetic algorithms, and Bayesian networks[10~13]. The merit of these methodologies, which can be also the demerit, is to use heuristic approach. In early 90's, various expert systems were developed as diagnosis tools but artificial intelligent or heuristic diagnosis systems have been emerged due to the lack of flexibility and the inherent uncertainty in expert systems. They made a remarkable progress in diagnosis field, while authors had the difficulty to introduce them to actual power plants. The reason was that the efficiency staff in power plant did not allow the black-box model in actual applications. Even though Bayesian network is not a black-box model, the heuristic process in the decision of prior or conditional probabilities was pointed out as the same reason. Efficiency staff wants to get a pin-point diagnosis tool based on the basis of intuitive and understandable concept. Authors tried to give the information about ‘which component is the root cause’ and ‘how much influential the root cause is to other components’. Also this information should depend on the First law of thermodynamics and be able to connect with the performance test results. The diagnosis methodology proposed in this study is based on the simple algebra. To connect the turbine cycle performance tests, it concentrates on the quantitative identification of root-cause degradation and its effect to other components, under consideration by the First law of thermodynamics. Authors will demonstrate a proto-type model of the diagnosis tool.

II. Derivation of a Mathematical Model

II.1 Correlation of Performance Indices

The turbine cycle in NPPs has the representative structure of large-scale steam turbine cycle. Figure 1 shows the schematic turbine cycle piping & instrumentation diagram of Gori NPP unit 3&4 under consideration in this study. The performance of turbine cycle is determined by boundary conditions and the performance of components. The boundary condition means something that can be regarded as surrounding conditions outside the turbine cycle boundary, which has influence upon turbine cycle behavior and its example is main steam condition, atmospheric pressure and temperature, condenser cooling sea water temperature, and so on. The performance index of a component means the degree of functional satisfaction. Each component has its own performance index. For example, a turbine has the efficiency that is the ratio of actual enthalpy drop and isentropic enthalpy drop as a performance index. In case of a heat exchanger, heat transfer coefficient may be a performance index. Electric output can be considered as the performance index of a generator.

Through the investigation of turbine cycle behavior, authors concluded that these performance indices were determined by two factors. The one is the degradation of the component itself. In this study, it is defined as ‘self-degradation’. The damage of turbine blades makes turbine efficiency lower. The tube plugging of heat exchanger decreases heat transfer area, so the overall performance of the heat exchanger is decreased eventually. The other factor is the impact of the performance of other components. The relation between any two performance indices is very complex. The increase of the performance index of a component may cause the performance of other components to increase, decrease, or keep no change. From the wide viewpoint, the boundary condition can be also considered as the performance index of surroundings. The boundary condition has influence on the change of the performance of components, too. In NPPs, the SG thermal output usually keeps constant, so the whole performance indices in turbine cycle are adjusted according to the SG thermal output. The condenser cooling sea water temperature is another important boundary condition. The performance of a condenser as well as LP FWHs is strongly influenced by sea water temperature. In conclusion, overall turbine cycle performance is determined by the performance of components and boundary conditions, and the performance of components is closely coupled as shown in Figure 2.

II.2 Mathematical Background

In this section, the mathematical model to find the self-degraded components, though we don't know why they are degraded, will be derived using the correlation among performance indices and algebraic expressions. In this model, three types of degradation were defined according to the physical characteristic of degradation. Intrinsic degradation ΔP_i^I is defined as the performance change caused by the self-degradation in a component *i*. Induced degradation ΔP_i^U is defined as the sum of the performance change caused by the performance of other components or boundary conditions in a component *i*. Superficial degradation ΔP_i^S is defined as the sum of ΔP_i^I and ΔP_i^U:

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

where $\Delta P_i = P_{i,operation} - P_{i,design}$,

$P_{i,operation}$ is the performance index of a component *i* in an operating condition,

$P_{i,design}$ is the performance index of a component *i* in a design condition.

Authors defined the assumption of Equation (1) as 'superposition rule'. We usually think that the state of a system may be optimum if all the components have their design performance indices. The superposition rule explains that the deviation from a design performance index is the linear combination of the effect of each degraded component. In real world, we can observe the only superficial degradation. In other words, we cannot distinguish the intrinsic and induced degradation separately. If we identify the quantity of the intrinsic degradation, we may be able to say which component is the root cause.

Let's assume the simple turbine cycle model with two components as shown in Figure 3 to represent the induced degradation as a function of the intrinsic degradation. In Figure 3, there are component *i* and *j*. Each component has its own performance index P_i and P_j. As explained above, each performance index may influence on the performance indices of other components. In the model, it is assumed that the influence between the performance indices of components is based on the first order linear relation within the near range of the design performance indices:

$$P_j = \beta_{ij} + w_{ij} P_i , \tag{2}$$

where w_{ij} is a linear regression coefficient and means the magnitude of influence,
β_{ij} is the intercept.

Actually the correction curves in the performance procedures used in NPPs as well as fossi-fuel plants show the linear relation between the performance indices of major components and electric output, and this fact supports the rationale of the above assumption[14~16]. Now, the induced degradation, ΔP_i^U is derived using the Equation (1) and (2) in Equation (3). As mentioned, the intrinsic degradation is caused by self-degradation, so it is independent to others.

$$\Delta P_i^U = \sum_{j \neq i} w_{ji} \Delta P_j^I \, . \tag{3}$$

Eventually this is the extensive concept of the superposition rule. This assumption will be validated in the next section. Therefore the superficial degradation, ΔP_i^S which we can only observe in the performance tests is derived:

$$\Delta P_i^S = \Delta P_i^I + \sum_{j \neq i} w_{ji} \Delta P_j^I \, . \tag{4}$$

If we assume that w_{ii} is 1.000 conceptually, we can simplify Equation (4) as follows:

$$\Delta P_i^S = \sum w_{ji} \Delta P_j^I \, . \tag{5}$$

After all, Equation (5) is a kind of simultaneous equations of which the total number is *i*. However w_{ji} can cover only a part of the variability among the performance indices approximately. That is, we cannot solve Equation (5) explicitly. We must find the set of estimated ΔP_j^Is to satisfy Equation (5) as closely as possible. Therefore we need the loss function to find a numerical solution. Authors suggested Equation (6) as one of the simple loss functions of ΔP_i^S.

$$f(\Delta\vec{P}^I) = \sum_i (\Delta P^S_{i,observe} - \Delta P^S_{i,estimate})^2 \\ = \sum_i (\Delta P^S_{i,observe} - \sum_j w_{ji} \Delta P^I_j)^2 , \quad (6)$$

where $\Delta P^S_{i,observe}$ is the observed superficial degradation of component *i*,

$\Delta P^S_{i,estimate}$ is the estimated superficial degradation of component *i*.

$\Delta P^S_{i,observe}$ and w_{ji} are the known quantity as stated above. On the other hand, $\Delta P^S_{i,estimate}$ is the function of ΔP^I_i and the unknown quantity. Therefore the finding of the intrinsic degradations is the same as the minimization of the loss function *f*. If we find the set, $\Delta\vec{P}^I = \left(\Delta P^I_1, \Delta P^I_2, ..., \Delta P^I_n\right)$ to minimize Equation (6), we can regard this set as the intrinsic degradation state of turbine cycle.

III. Validation Results

This section will describe the validation of the superposition rule and the overall capability of the diagnosis module.

III.1 Validation of the Superposition Rule

In order to easily validate the superposition rule, a simplified turbine cycle model was constructed by the PEPSE, one of the commercial steam turbine cycle simulation toolbox according to the schematic diagram of Figure 4[17]. This model includes a LPT last stage, a condenser, and a LP FWH. Three components are physically connected by piping network, we can imagine their degradation may influence on the performance indices of other components. Table I shows the simulation results under four plant conditions. The second column, $P_{i,design}$ shows the results when the design performance indices are inputted. To observe the change of various performance indices, several performance indices at the respective component were selected. From the third column to the fifth column, the results under the intrinsic degradation state of each component were shown. In the first test case, authors modified the LPT efficiency to make an intrinsic degradation state for the LPT. In the second and the third case, the heat transfer area of the LP FWH and the condenser were decreased respectively. Table II shows another simulation result and the estimated result using the superposition rule for component 3, the condenser. The second and the fourth columns in Table II correspond to the results under multiple degradation conditions. The second column is the performance indices of the condenser when the LPT and the LP FHW are degraded simultaneously. The fourth column is the performance indices of the condenser when all the three components are degraded together. The third and the fifth columns are the algbraically estimated results, which means the simple summation of the deviation between performance indices, using only Table I. If Equation (5) is valid, the values of the second and fourth column should be the same as that of third and fifth column respectively. If the LPT and the LP FWH are degraded, the only induced degradation caused by both components should appear as the summation in the condenser. In the meanwhile, in the fifth column, the induced degradation caused by the LPT and the LP FWH, and the intrinsic degradation caused by the condenser should appear, too. Through the results in Table II, authors could conclude the validity of the superposition rule.

But the cautious point to apply the superposition rule is that this is only valid in near range of the design performance index. We cannot assure the linearity of performance indices on the whole operating range, and this can be identified in the correction curves as mentioned. However, fortunately, the interest in the performance tests may be focused on the degradation within maximum ~20%. The superposition rule seems to be applied in this rage.

III.2 Demonstration of the Diagnosis Module

For the overall demonstration, authors used the simulation model constructed by the PEPSE again. The essential role of this model is to analyze regression coefficient, w_{ji}. Of course, it is theoretically reasonable to get w_{ji} from the actual plant data, but we cannot control plant conditions arbitrarily and degrade a component intentionally. In this case, it is a general approach to use a simulation model.

The target plant was decided to Gori NPP unit 3&4 which pipe & instrumentation diagram was shown in Figure 1. This model was constructed on the basis of the 100% rated electric output heat balance diagram which was provided turbine vendor, General Electric. Then the representative performance index of each component is decided as shown in Table III. To get the useful w_{ji}, we must do our best to carry out the simulation under various intrinsic degradation states as extensively as possible. Authors collected the information about the root-cause causing the intrinsic degradation from literature survey[18, 19] and the interview with efficiency staff. Table IV is the correlation matrix analyzed from the simulation results. The rows are independent parameter, P_i and the columns are dependent parameters, P_j in Equation (1). As shown in Table IV, most of the correlation coefficients are larger than 0.500. This is another evidence that two performance indices have linear relation. We can get w_{ji} using the least square method using Table IV.

To identify the capability of the proposed diagnosis module under the intrinsic degradation of multiple components, the test matrix of Table V was prepared. The results from the simulation using the test matrix were considered as observed performance indices. Figure 5 shows the diagnosis results of the proposed module. The horizontal axis means the name of component, and the vertical axis is the difference between the observed and the estimated intrinsic degradation in Figure 5. All the performance indices are normalized by dividing to design performance indices. We could found the estimated intrinsic degradation state by adjusting the intrinsic degradation of each component and minimizing the loss function of Equation (6). ‘Observed performance indices’ in this figure corresponds to the intrinsic degradation when single component is degraded. Figure 5 shows the proposed diagnosis module is able to find which component is the root cause on the basis of the algebraic model.

IV. Discussions and Conclusions

The eventual purpose of the diagnosis may be the economical management of power plants. In the operating plants as well as the plants to be designed, the reduction of operating cost is the important topic to compete other electric power sources. Until now, a number of diagnosis methodologies have been proposed, but the example of nuclear industrial application is not so common because of the safety culture that makes much account of proven technology, which is important concept for nuclear safety. From this viewpoint, the diagnosis methodology that has practically enough accuracy as well as is derived simply and clearly can meet the requirements of nuclear diagnosis system.

The essential concept of the proposed model is the superposition rule of degradation phenomena. Though the superposition rule is not so significant statistically, almost of the performance indices were fairly compatible with this model. Also we can perform ‘what-if’ analysis in order to observe the behavior of turbine cycle when some performance indices are changed. If the superposition rule based on the linear relation is upgraded realistically, and the more meaningful loss function is proposed, the algebraic model may be much beneficial to efficiency staff as well as turbine cycle designer.

Acknowledgement

This study is sponsored from the center for Korea Nuclear Instrumentation and Control System.

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Table I. Simulation results to validate the superposition rule

	$P_{i,design}$	**(1) LPT efficiency changing**	**(2) LP FWH plugging**	**(3) Condenser plugging**
LPT (P_1)				
Efficiency (-)	0.7553	0.7816*	0.7553	0.7555
LP FWH (P_2)				
Condensing region heat transfer rate (W/°C)	9.38E+06	9.26E+06	9.35E+06*	9.39E+06
Drain cooling region heat transfer rate (W/°C)	2.03E+06	2.03E+06	1.98E+06*	2.03E+06
Heat transfer effectiveness (-)	0.95	0.94	0.94*	0.95
Terminal temperature difference (°C)	2.78	2.85	2.80*	2.77
Drain cooler approach (°C)	5.60	5.60	5.80*	5.50
Condenser (P_3)				
Condensing region heat transfer rate (W/°C)	2.68E+08	2.68E+08	2.68E+08	2.64E+08*
Drain cooling region heat transfer rate (W/°C)	2.53E+06	2.57E+06	2.55E+06	2.51E+06*
Heat transfer effectiveness (-)	0.97	0.97	0.97	0.97*
Terminal temperature difference (°C)	2.88	2.85	2.88	2.94*
Back pressure (mmHg)	38.1	37.8	38.1	38.3*

* Intrinsic degradation, others are the results of induced degradation.

Table II. Validation results for the superposition rule

Condenser (P_3)	Simulated (1) and (2)	Estimated	Simulated (1) , (2) and (3)	Estimated
Condensing region heat transfer rate (W/°C)	2.68E+08	2.68E+08	2.64E+08	2.64E+08
Drain cooling region heat transfer rate (W/°C)	2.59E+06	2.59E+06	2.56E+06	2.57E+06
Heat transfer effectiveness (-)	0.97	0.97	0.97	0.97
Terminal temperature difference (°C)	2.85	2.85	2.94	2.94
Back pressure (mmHg)	37.8	37.8	38.0	38.0

* (1), (2), and (3) were defined in Table I.

Table III. Summary of the selected performance indices

Component types	Performance index	Definition
Turbine	Efficiency	Ratio of the actual enthalpy drop to the isentropic enthalpy drop
MS	Moisture separation effectiveness	Ratio of the moisture quantity at inlet to drain flowrate
Heat exchanger (RH and FWH)	Heat transfer effectiveness	Ratio of the achievable maximum temperature increase to the actual temperature increase
Condenser	Shell pressure	
Generator	Electric output	

Table IV. Correlation matrix for the performenace indices

P_j / P_i	HPT	LPT	MS	1st RH	2nd RH	Cond.	1st FWH	2nd FWH	3rd FWH	4th FWH	5th FWH	6th FWH
HPT	1.0000	1.0000	0.8668	1.0000	0.9153	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
LPT	N/N	1.0000	0.8659	0.8659	N/N	1.0000	1.0000	1.0000	1.0000	0.9923	0.8662	N/N
MS	1.0000	0.9999	1.0000	0.9989	1.0000	0.9997	0.9999	0.9999	0.9999	0.9998	0.9999	0.9999
1st RH	1.0000	0.9989	0.9192	1.0000	1.0000	0.4974	0.9930	0.9994	0.9999	0.9999	1.0000	1.0000
2nd RH	1.0000	0.9999	0.9203	1.0000	1.0000	0.4167	0.9996	1.0000	1.0000	1.0000	1.0000	1.0000
Cond.	0.9060	0.7492	0.5007	0.9476	0.9821	1.0000	0.9752	0.9605	0.9549	0.9548	0.9550	0.4818
1st FWH	0.2667	0.4755	0.3469	0.2330	0.2077	0.2731	1.0000	0.9411	0.9384	0.9252	0.0103	0.5261
2nd FWH	0.8991	0.1239	0.7712	0.9421	0.1858	0.3477	0.9002	1.0000	0.9842	0.9841	0.9912	0.9528
3rd FWH	0.8853	0.3395	N/N	0.9708	0.1563	0.3537	0.8384	0.9903	1.0000	0.9959	0.9990	0.9727
4th FWH	0.9884	0.7821	N/N	0.9896	0.9762	0.3765	0.9962	0.9940	0.9925	1.0000	0.9918	0.9903
5th FWH	1.0000	0.6094	0.8590	1.0000	1.0000	0.5597	0.4917	0.9595	0.9963	0.9994	1.0000	1.0000
6th FWH	0.9948	0.4472	0.4783	0.9998	0.9973	0.6985	0.7449	0.9680	0.9908	0.9958	0.9876	1.0000

'N/N' is no relation between two performance indices.

Table V. Test cases for the validation of the diagnosis module

Test case	Modified parameters	Design value	Testing Value
1	2nd HP FWH, plugged tube number	0%	3%
	3rd HP FWH, plugged tube number	0%	2.5%
2	Condenser, plugged tube number	0%	0.5%
	1st LP FWH, plugged tube number	0%	3.5%
	2nd LP FWH, plugged tube number	0%	4.5%

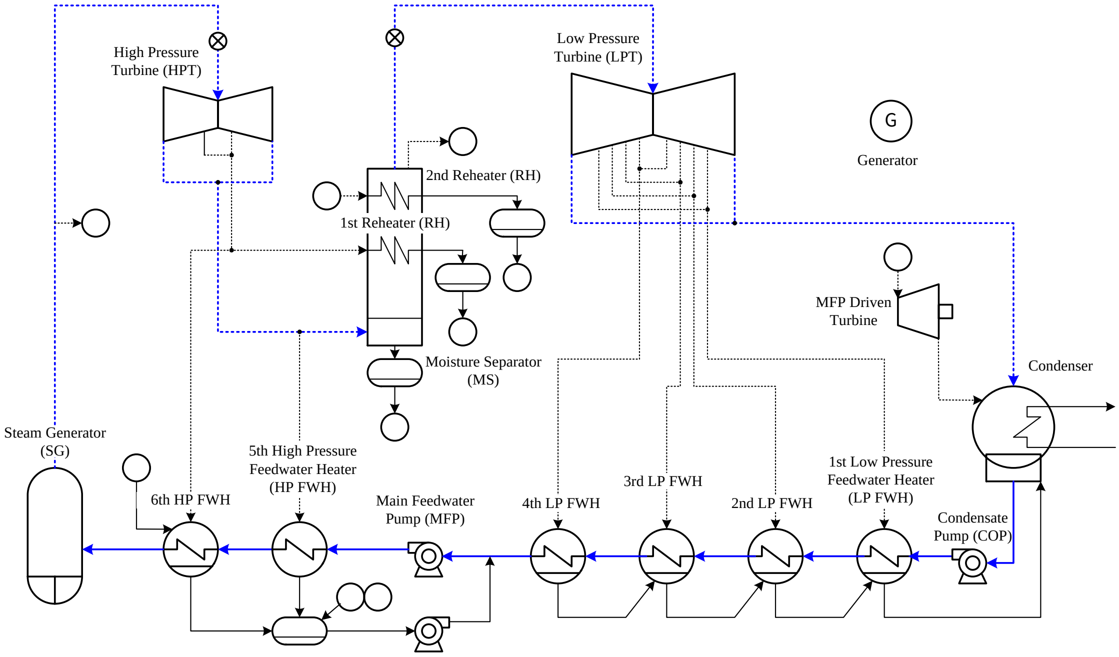

Figure 1. Piping & instrumentation diagram of Gori NPP unit 3&4

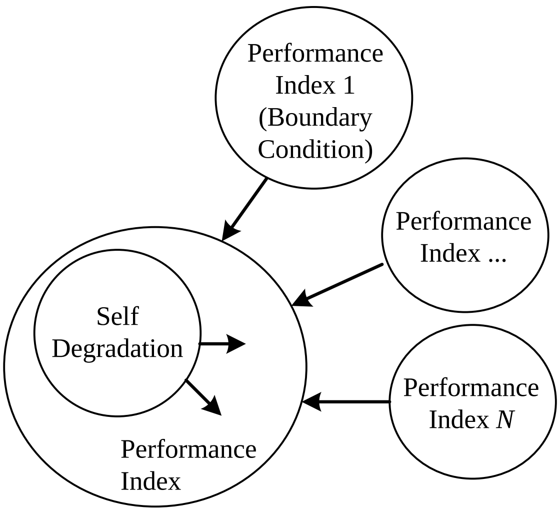

Figure 2. Relation between the performance indices and boundary conditions

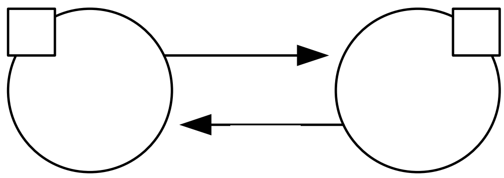

Figure 3. Mathematical model for the influence of component degradation

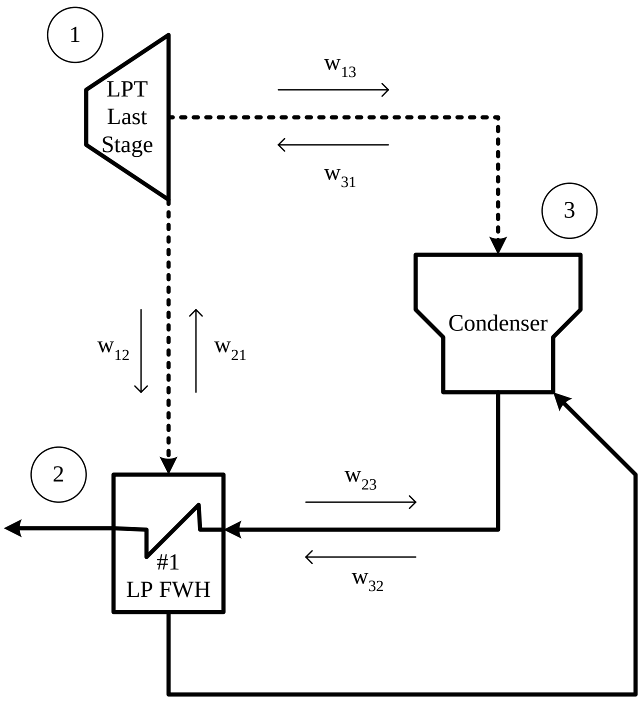

Figure 4. Simplified turbine cycle model for the validation of the superposition rule

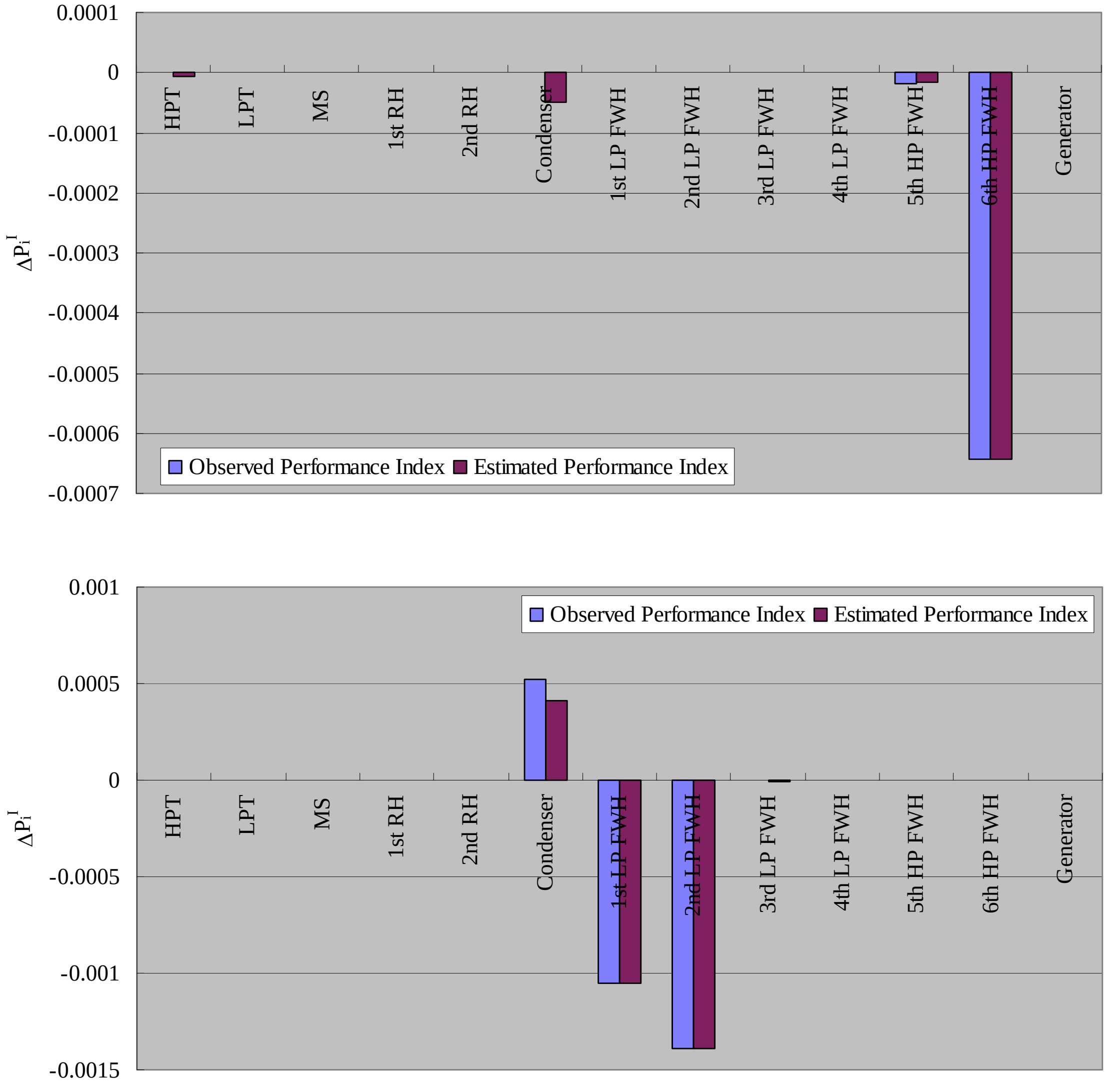

Figure 5. Validation results for the diagnosis module (the intrinsic degradation, upper: case 1, and lower: case 2)