Expert Systems with Applications 29 (2005) 747–756

Expert Systems with Applications

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Advisory system for the diagnosis of lost electric output in nuclear power plants

Gyunyoung Heo[a,*], Soon Heung Chang[a], Seong Soo Choi[b], Gwang Hee Choi[c], Moon Hak Jee[c]

[a]Korea Advanced Institute of Science and Technology, Department of Nuclear and Quantum Engineering, 373-1 Guseong-dong, Yuseong-gu, Daejeon 305-701, South Korea
[b]Atomic Creative Technology, Inc.1688-5 Shinil-dong, Deaduk-gu, Daejeon, South Korea
[c]Korea Power Electric Research Institute,103-16 Moonji-dong, Yuseong-gu, Daejeon, South Korea

Abstract

The enhancement of efficiency is world-wide trend to survive under intense competition. In recent years, the efficiency in the power industry is also one of the important topics. In case of nuclear power plants(NPPs), the period and quality of maintenance is an especially important factor to increase efficiency as well as availability. Therefore, the accurate identification of the root causes for lost electric output is indispensable to decrease the period and to increase quality of maintenance. The diagnosis in NPPs is more difficult because the turbine cycle of NPPs uses saturated steam as working fluid. In this study, authors tried to develop an advisory system with the quantitative diagnosis model consisting of statistical regression analysis and Bayesian network for the support of nuclear turbine cycle diagnosis. The proposed advisory system includes the knowledge-base representing the normal or abnormal behavior of nuclear turbine cycle. Authors selected 34 boundary parameters that independently influence to electric output. Using the data collected from a turbine cycle simulation tool, the statistical correlation between a boundary parameter and electric output was analyzed. To give the belief, that is the degree of accuracy, of root causes under various uncertainty sources, belief module for the boundary parameters is developed on the basis of Bayesian network. In conclusion, this diagnosis module can give the impacts of the root causes and their uncertainty simultaneously, so we call it 'Lost MW calculator'. After the validation using simulated data and actual performance data, this module was installed in Younggwang NPP units 3 and 4 in Korea.

Keywords: Advisory system; Bayesian network; Regression; Turbine cycle; Diagnosis; Nuclear power plant

1. Introduction

Until now, the efficiency of nuclear power plants(NPPs) is being focused on the enhancement of nuclear reactors such as power up-rating. However the concern about the efficiency of turbine cycle is being increased under deregulation environment. To propose overall concept of efficiency enhancement of turbine cycle in NPPs, authors tried to make a technical road-map for the long-term research planning (Heo, 2004). In the technical road-map, we indicated the accurate and rapid identification of the root cause of lost electric output as the one of the essential items, because the period and quality of maintenance is an especially important factor as well as availability due to long-term operation in case of NPPs. However the identification of the root cause is not so easy because of the complexity of turbine cycle itself. Moreover, since saturated steam used as working fluid in NPPs make the performance analysis less reliable, even observation of performance degradation is not clear. Even if there is no definite solution yet, for a long time many researches have suggested the various approaches. As a diagnosis method about complex energy systems, thermoeconomic analysis was proposed (Frangopoulos, 1987; Lozano et al., 1993; Torres Valero, Serra, & Royoet al., 2002). This methodology suggested the detail procedures for energy as well as exergy flow of thermal systems such as a power plant or a chemical plant. The concept merging thermodynamic

* Corresponding author.Tel.: +82 428 693 891; fax: +82 428 693 810.
E-mail addresses: ad0ngtic@kaist.ac.kr (G. Heo), shchang@kaist.ac.kr (S.H. Chang).

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doi:10.1016/j.eswa.2005.06.002

properties and cost made the cost-benefit evaluation possible. However it is difficult to describe the uncertainty in diagnosis since it is a kind of deterministic approach. Aside from deterministic approach, a lot of heuristic or probabilistic diagnosis methods have been proposed. As the applications to turbine cycle in NPPs, there were neural networks, genetic algorithms, and Bayesian networks (Arroyo-Figueroa, Alvarez, & Sucar, 2000; Guglielmi, Parisini, & Rossi, 1995; Kang & Golay, 1999; Yangping, Bingquan, & DongXin, 2000). The advantage of these methodologies, which can be also the demerit, is to use heuristic approach. In early 90's, various expert systems were developed but artificial intelligent, heuristic, or probabilistic diagnosis systems have been emerged to enhance flexibility or to reflect uncertainty in expert systems. They made remarkable progress in diagnosis field, but authors had difficulty in introducing them to actual power plants. The reason was turbine operator in power plants did not allow the black-box model in actual applications. Even though Bayesian network is based on statistical approach, the heuristic aspect during the decision of prior or conditional probabilities was pointed out as one of the bottlenecks. As commercial products which objective is industrial application, the representative examples are 'EfficiencyMap™' of General Electric Enter software, 'PMAX®' of Scientech software, 'EtaPro™' of General Physics. The commercial products were based on statistical analysis and inference rather than heuristic technique for industrial application. But almost of the turbine operators mainly depend on their experience because of the financial difficulty in installing tools and the doubt for effectiveness of commercial products.

In this study, the advisory system, which is called 'Lost MW calculator', was developed on the web, which has simple concept and intuitive approach in order to increase practicality in the process of nuclear turbine cycle diagnosis. The developed module is based on the assumption that there may be various kinds of uncertainty in diagnosis. Therefore this module was designed to provide the quantitative impact of the probable root cause as well as its degree of belief. To analyze the quantitative impact of the root causes, regression analysis was used on the basis of the sensitivity analysis between the probable root cause and electric output. To evaluate the degree of belief, authors used Bayesian network which can organize knowledge-base under uncertainty.

2. Development strategies

The overall structure of Lost MW Calculator is shown in Fig. 1.The core module of Lost MW Calculator uses the data generated from turbine cycle simulation model. To get the information about the impact of root causes, the data goes through correlation analysis and regression analysis. To infer the belief of root causes, Bayesian network is constructed. At this time, the results of correlation analysis are used. If real plant data is inputted into Lost MW Calculator, the impact and the belief are calculated.

2.1. Simulation and data preparation

The purpose of Lost MW Calculator, as stated in introduction, is two things. The one is to provide the lost electric output of each degradation cause, and the other is to provide the belief for the lost electric output calculated. These functions should be based on the behavior of actual plants. However it is impossible to control the plant arbitrarily or to degrade a component intentionally. In this case, it is a general approach to use a simulation code. Authors used a turbine cycle simulation tool, PEPSE, which is made by Scientech Corporation. PEPSE is a one-dimensional thermodynamic code, and can simulate generic steam turbine cycle using the component and stream models. PEPSE can also simulate the behavior under various boundary conditions. The target plant was selected to Younggwang NPP units 3 and 4 that is the Korean standard NPPs. The turbine cycle model was developed using the design mode of PEPSE on the basis of the 100% power heat balance diagram which was submitted from turbine cycle vendor, General Electric (Alder, Blakeley, Fleming, & Kettenacker, 1999). The validation of the developed model was achieved through two steps. In the first step, the validation for each component was carried out. In this step, authors checked the consistency between simulated thermo-hydraulic properties such as pressure or

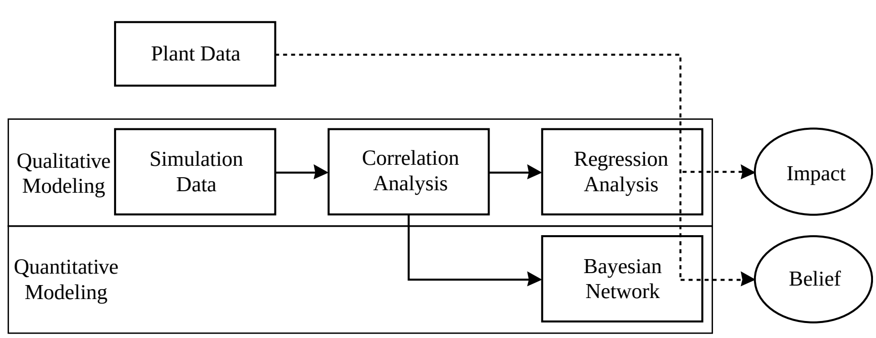

Fig. 1. Overall structure of Lost MW Calculator.

temperature at component inlet and outlet and the design specifications of each component. In the second step, authors checked thermo-hydraulic balance at cycle level. Electric output and heat rate, performance indices of components, and turbine expansion line which is called as ‘Enthalpy-Entropy diagram’ or ‘Mollier diagram’ are the checking points. Through two validations, authors regarded that the data from the turbine cycle model is accurate enough to substitute for actual plant data. Fig. 2 shows the turbine cycle model made by PEPSE and the position of major components. In Fig. 2, the major components of a turbine cycle are represented by circles.

To simulate the turbine cycle model as extensively as possible, the parameters to independently influence electric output were selected through the literature survey, interview with turbine operators or efficiency staff, and engineering judgment (Eckert, 1998; KEPRI, 1995). These parameters are defined as boundary parameters in this study. The value of boundary parameters is input to each component in the PEPSE turbine cycle model. Totally 34 boundary parameters were selected and are shown in Table 1 with their design value and the physically variable range. At least one more boundary parameters for a component were selected. The data for the development of Lost MW Calculator was generated by repeated simulations which are performed by changing the boundary parameters within the variable range. We will call this data set as reference data.

2.2. Sensitivity analysis

The purpose of sensitivity analysis is to analyze the relation between a boundary parameter and electric output. In this paper, sensitivity analysis is composed of the reference data, correlation analysis, and regression analysis in Fig. 1. Let’s assume an independent variable is X_i and a dependent variable is Y_i. If the maximum order of correlation is n, we can derive a polynomial regression model like Eq. (1).

$$Y_i = \beta_{i,0}X_i^0 + \beta_{i,1}X_i^1 + \ldots + \beta_{i,n}X_i^n \tag{1}$$

where β is regression coefficient.

If the number of the reference data is m, Eq. (1) can be represented by matrix form like Eq. (2).

$$\begin{bmatrix} Y_{i,1} \\ Y_{i,2} \\ \cdots \\ Y_{i,m} \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} \beta_{i,0} & \beta_{i,1} & \ldots & \beta_{i,n} \end{bmatrix} \begin{bmatrix} X_{i,1}^0 & X_{i,1}^0 & \ldots & X_{i,1}^0 \\ X_{i,1}^1 & X_{i,2}^1 & \ldots & X_{i,m}^1 \\ \cdots & \cdots & \cdots & \cdots \\ X_{i,1}^n & X_{i,2}^n & \ldots & X_{i,m}^n \end{bmatrix} \tag{2}$$

In this study, an independent variable becomes a boundary parameter, and a dependent variable is electric output. We can find an estimator, $[\hat{\beta}_{i,0} \quad \hat{\beta}_{i,1} \quad \ldots \quad \hat{\beta}_{i,n}]$ using the least square method. The order of a polynomial correlation is determined by the statistics R^2 like Eq. (3).

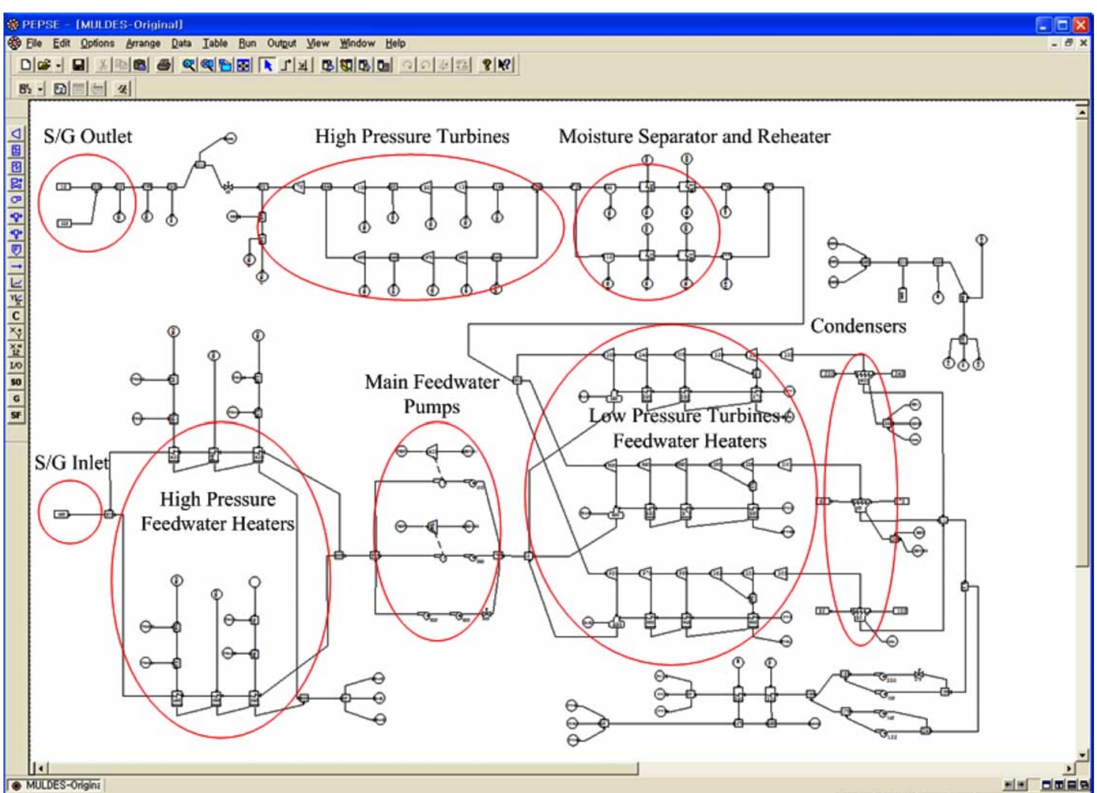

Fig. 2. The simulation model of Younggwang NPP units 3 and 4 constructed by PEPSE.

Table 1
Summary of boundary parameters

Boundary parameters	Unit	Design value	Lower value	Upper value
Steam generator quality	–	0.9955	0.99	0.999
Feedwater flowrate	lbm/h	6358750	6231575	6422337.5
Cooling sea water temperature	°F	67.9	47.53	88.27
Cooling sea water flowrate	lbm/h	101165000	91048500	111281500
Number of condenser tubes	–	26678	24000	26678
Condenser cleanness factor	–	0	0.765	0.935
Condenser pump discharge pressure	psia	200	180	220
Condenser pump efficiency	–	0.86	0.774	0.86
Feedwater pump discharge pressure	psia	1100	999	1221
Feedwater pump efficiency	–	0.8125	0.73125	0.8125
Moisture separator efficiency	–	0.9685	0.94913	0.9685
1st Reheater tube conductivity	btu/h ft °F	12.8	10.24	12.8
1st Reheater heat transfer area	ft^2	58819.5	47055.6	58819.5
2nd Reheater tube conductivity	btu/h ft °F	12.8	10.24	12.8
2nd Reheater heat transfer area	ft^2	43520.8	34816.64	43520.8
1st LP feedwater heater tube conductivity	btu/h ft °F	8.7	6.96	10.44
1st LP feedwater tube number	–	1051	950	1051
2nd LP feedwater heater tube conductivity	btu/h ft °F	9.2	7.36	11.04
2nd LP feedwater tube number	–	705	630	705
3rd LP feedwater heater tube conductivity	btu/h ft °F	9.5	7.6	11.4
3rd LP feedwater tube number	–	559	500	559
1st HP feedwater heater tube conductivity	btu/h ft °F	9.8	7.84	11.76
1st HP feedwater tube number	–	2683	2400	2683
2nd HP feedwater heater tube conductivity	btu/hr ft °F	10.2	8.16	12.24
2nd HP feedwater tube number	–	2456	2300	2456
3rd HP feedwater heater tube conductivity	btu/hr ft °F	10.5	8.4	12.6
3rd HP feedwater tube number	–	2511	2400	2511
All the turbine extraction line pressure drop	–	0.03	0.03	0.05

$$R_i^2 = \frac{\sum_{k=1}^{m}(\hat{Y}_{i,k} - \bar{Y}_i)^2}{\sum_{k=1}^{m}(Y_{i,k} - \bar{Y}_i)^2} \quad (3)$$

where

$$\hat{Y}_{i,k} = \sum_{j=0}^{n} \hat{\beta}_{i,j} X_{i,k}^{j} \text{ and } \bar{Y}_i = \frac{\sum_{k=1}^{m} Y_k}{m},$$

i is ith boundary parameter.

The order was fixed when R^2 exceeded 99%. However the order of all the correlations did not exceed maximum 3 orders. Fig. 3 shows the sensitivity analysis results of steam generator outlet steam moisture and cooling sea water temperature, which they are the representative boundary parameters. The vertical axis means the normalized electric output or heat rate that is the reciprocal number of the electric output. That is, the vertical axis represents the dependant variable. The horizontal axis means a boundary parameter, the independent variable. In case of the upper figure, the horizontal axis is the normalized steam moisture at steam generator outlet. Electric output decreases as the amount of steam moisture increases linearly. In case of the lower figure, the horizontal axis is the temperature of condenser cooling sea water. Electric output increase or decrease as the temperature of cooling sea water increases non-linearly. All of the boundary parameters could be covered by maximum 3-order polynomial. Like Fig. 3, we finished sensitivity analysis for total 34 boundary parameters, and derived regressed equations.

2.3. Diagnosis using Bayesian network

The results of sensitivity analysis provide quantitative relationship that is the impact of each boundary parameter to electric output. However the uncertainty during performance test and analysis which is the process of data acquisition or performance index calculation may damage to the reliability of sensitivity analysis. In this study, authors divided the uncertainty in performance diagnosis into two categories. The one is the uncertainty of a parameter itself. The uncertainty in data acquisition belongs to this category. The other is the uncertainty on the relation among the parameters. The boundary parameters were selected considering mutual independency but if two or more boundary parameters are changed together, the mixing behavior is not independent still more. For the inference under uncertainty situation, authors selected Bayesian network as a tool of the construction of knowledge-base for diagnosis. Several researchers have been already carried out the diagnosis using network-type knowledge-base in a complex system. Bhushan and Rengaswamy (2002a,b) and Kang et al. (1999, 2000) applied network-type knowledge-base to industrial facilities. Because the diagnosis in this study should be achieved from the overall turbine cycle

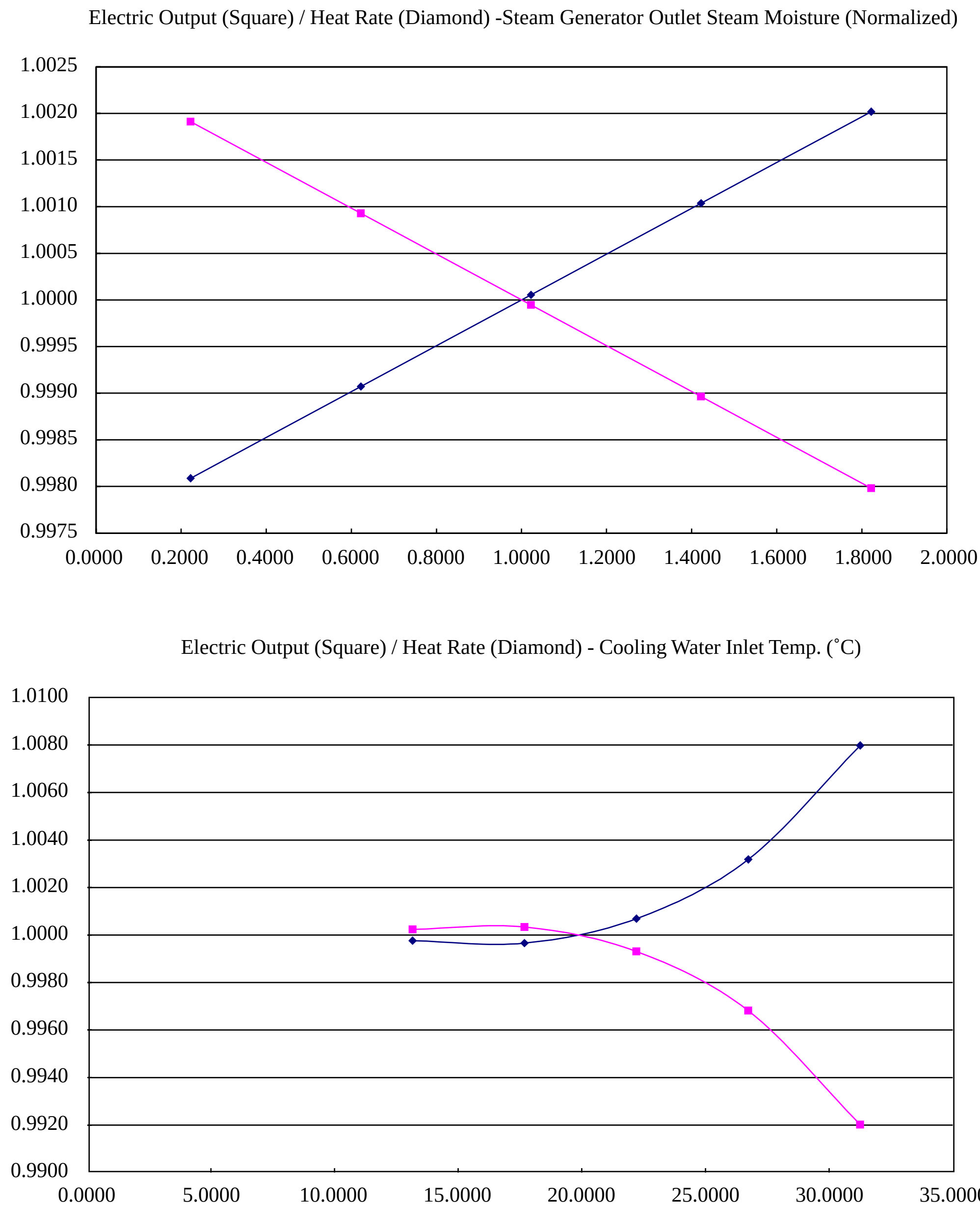

Fig. 3. Sensitivity study results for steam generator outlet moisture (upper) and cooling sea water temperature (lower).

viewpoint, the knowledge-base was constructed using the proposed boundary parameters.

The detail procedure of making Bayesian network was already published (Jensen, 1996), but authors will briefly describe the specific step to be applied to this study. The knowledge-base using Bayesian network is made through two steps; qualitative modeling and quantitative modeling. The purpose of qualitative modeling is to identify cause-consequence relation, and the purpose of quantitative modeling is to allocate necessary probabilities. In Fig. 4, there is a simple Bayesian network model with three nodes and arrows. Bayesian network consists of nodes and arrows. A node represents a parameter or a variable, and an acyclic arrow means cause-consequence relation. The hypothesis variable is defined as the event that is not observable or only observable at an unacceptable cost. Usually a causal parameter corresponds to the hypothesis variable. The information variable is defined as achievable information which may reveal something about the state of the hypothesis variables. A consequential parameter corresponds to the information variable. The variables in a model which are neither hypothesis variables nor information variables are called mediating variables. The mediating variable is used to re-organize cause-consequence relation effectively or to reflect specific characteristic of a problem. In the qualitative modeling, the structure of a network is decided and the knowledge-base is made using the variables and arrows. In the quantitative modeling, the prior

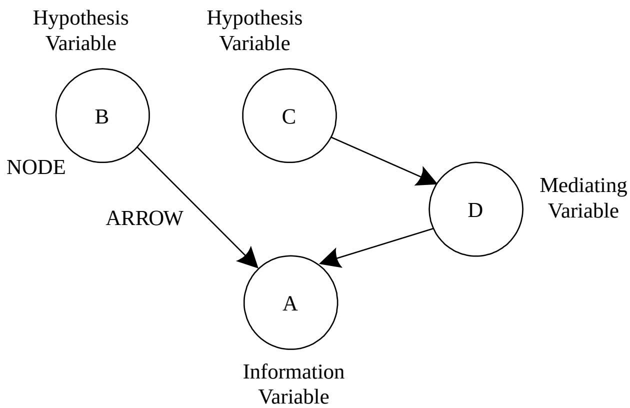

Fig. 4. A simple Bayesian network model.

probability is inputted to the hypothesis variable and the conditional probability is inputted to the arrow which represents cause-consequence relation between two variables.

The knowledge-base constructed by Bayesian network for Younggwang NPP turbine cycle in Korea is shown in Fig. 5. Authors assume there is the uncertainty in the boundary parameters, so the boundary parameters were defined as the hypothesis variables. However electric output was considered as accurate measurement comparing to other boundary parameters, so it was regarded as the unique information variable in this model. And we added some mediating variables for clear knowledge-base. For the decision of network structure, we must consider the relation between the hypothesis variable and the information variables. We can infer the state of the hypothesis variables if and only if the information variable receives the evidence, either electric gain or loss, because the hypothesis variables are mutually dependant after receiving the evidence. We call this phenomena conditional dependence and this kind of model is one of the typical converging connection problems (Jensen, 1996). In Fig. 4, if 'A' changes certainty, it opens communication between its parents, 'B' and 'C'. Similarly, in Fig. 5, we can see all of the hypothesis variables converge to the information variable. Actually this knowledge-base was implemented by using a Bayesian network toolbox, MSBNx Kadie et al., 2001.

The input of the prior probability and the conditional probability is the major work in quantitative modeling. The prior probability is inputted to the hypothesis variables as the uncertainty for the abnormality of boundary parameters. The prior probability will be changed to the posterior probability that is called belief or possibility through the inference process using the evidence of information variable. In the meanwhile, the conditional probability is inputted to the arrow to provide the strength of the relation between two variables. The prior probability is determined

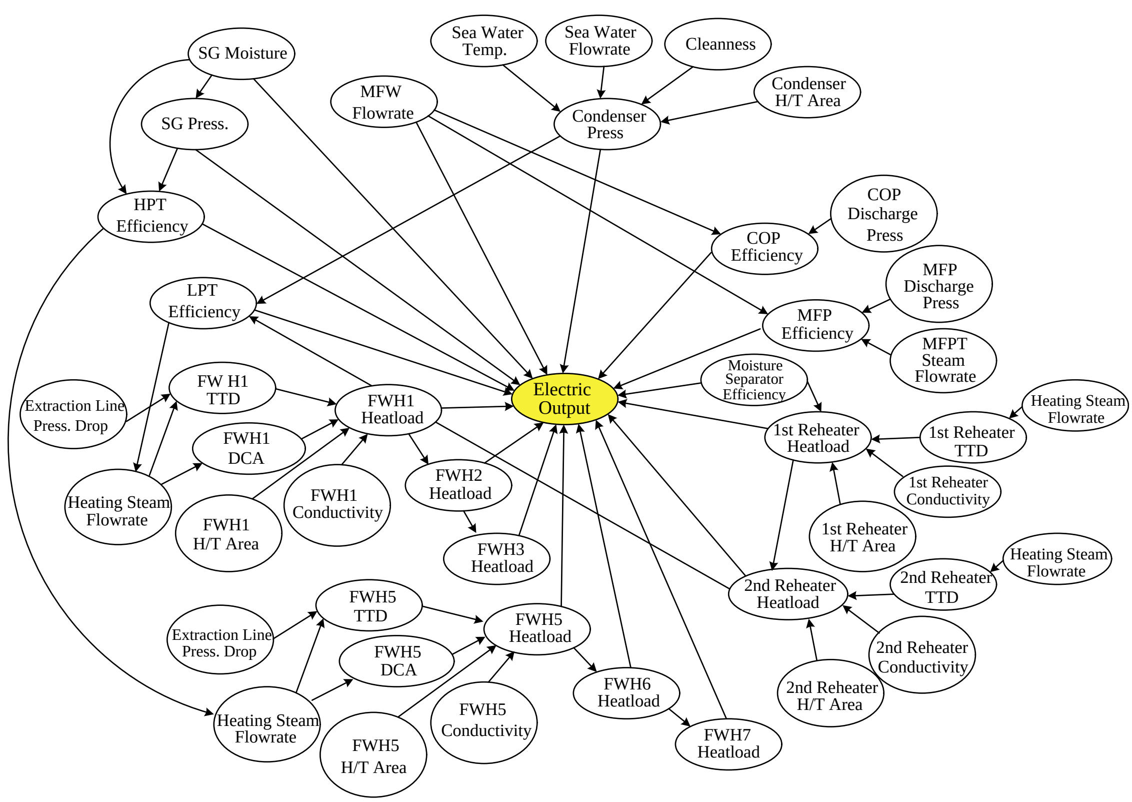

Fig. 5. Knowledge-base expressed by Bayesian network. (SG: Steam generator, HPT: High pressure turbine, LPT: Low pressure turbine, MFW: Main feedwater, H/T: Heat transfer, COP: Condenser pump, MFP: Main feedwater pump, MFPT: MFP turbine, TTD: Terminal temperature difference, DCA: Drain cooler approach, FWH: Feedwater heater).

Table 2
Conversion matrix for the prior probability

Expected electric gain or loss	Node state	Prior probability
5 kW	Abnormal	0.00
	Normal	1.00
1 kW	Abnormal	0.25
	Normal	0.75
0 kW	Abnormal	0.50
	Normal	0.50
−1 kW	Abnormal	0.75
	Normal	0.25
−5 kW	Abnormal	1.00
	Normal	0.00

by the deviation between a design value and an operating value, and the impact on electric output. The deviation can be taken from data acquisition, and the impact is provided from sensitivity analysis. Considering these factors, the prior probability is calculated according to Table 2. 'Expected electric gain or loss', ΔY_i, in Table 2 is calculated using Eq. (4),

$$\Delta Y_i = \sum_{j=0}^{m} \hat{\beta}_{i,j} X^j_{i,\text{ operating}} - \sum_{j=0}^{m} \hat{\beta}_{i,j} X^j_{i,\text{ design}} \tag{4}$$

where

$X^j_{i,\text{ operating}}$ is the value in test condition,
$X^j_{i,\text{ design}}$ is the value in design condition.

With interviewing with turbine operators or efficiency staff in power plants, authors decided prior probability criteria. For example, authors assumed that if the electric gain is more than 5 kW, the prior probability of 'abnormal' state of a boundary parameter is 0.000. The probability of 'normal' state is set to 1.000. If there is nothing in electric gain or loss, the both prior probabilities are the same since we cannot assure the boundary parameter's state. In this study, the prior probabilities are updated each turbine cycle performance test, and determined by being interpolated according to the Table 2.

The generation of the conditional probability used the results of correlation analysis. In the above section, authors simulated all kinds of probable behaviors that can be emerged in turbine cycle of an NPP, so we considered the correlation analyzed using the reference data as the conditional probability. The correlation coefficient and the conditional probability have the same concept from the viewpoint that both represent the relational strength. Let's assume the reference data are the universal set,

$$U = U(\vec{X}_1, \vec{X}_2, \ldots, \vec{X}_p) \tag{5}$$

where

$$\vec{X}_i = (X_{i,1}, X_{i,2}, \ldots, X_{i,m})$$

p is the number of boundary parameters, m is the number of simulations.

We can calculate the correlation coefficient r_{ij} between two parameters using Eqs. (6)–(8).

$$\bar{X}_i = \frac{\sum_{k=1}^{m} X_{i,k}}{m} \tag{6}$$

$$s_{ij} = \frac{\sum_{k=1}^{m} (X_{i,k} - \bar{X}_i)(X_{j,k} - \bar{X}_j)}{m-1} \tag{7}$$

$$r_{ij} = \frac{s_{ij}}{\sqrt{s_{ii} s_{jj}}} \tag{8}$$

where

$\bar{X}_i$ is mean of ith parameter,
s_{ij} is variance between ith parameter and jth parameter.

Physically the magnitude of r_{ij} is proportional to the degree of correlation, so the conditional probability is calculated on the basis of r_{ij} Table 3 shows the matrix for the calculation of the conditional probability. Authors assumed, for example, if r_{ij} is 1.000 and the state of a causal variable is 'abnormal', the state of the consequential variable is 'abnormal' because the tendency of two variable is the same. So authors determined the probability of 'abnormal' state is 1.000 and the probability of 'normal' is 0.000. If r_{ij} is zero, nobody can estimate the tendency. Therefore all of the probability should be the same. The range of the correlation coefficient is from −1.000 to 1.000, and that of probability is from 0.000 to 1.000. Therefore the range conversion is necessary when we interpolate the conditional probabilities.

Finally the inference is carried out after inputting the state of the information variable, electric output. If operating

Table 3
Conversion matrix for the conditional probability

r_{ij}	Conditional probability		
	Parent node	Child node	
1.00	Abnormal	Abnormal	1.00
		Normal	0.00
	Normal	Abnormal	0.00
		Normal	1.00
0.50	Abnormal	Abnormal	0.75
		Normal	0.25
	Normal	Abnormal	0.25
		Normal	0.75
0.00	Abnormal	Abnormal	0.50
		Normal	0.50
	Normal	Abnormal	0.50
		Normal	0.50
−0.50	Abnormal	Abnormal	0.25
		Normal	0.75
	Normal	Abnormal	0.75
		Normal	0.25
−1.00	Abnormal	Abnormal	0.00
		Normal	1.00
	Normal	Abnormal	1.00
		Normal	0.00

Table 4
Test cases for the validation of Lost MW calculator

Test case	Modified boundary parameters	Design value (%)	Operating value (%)
1	Cooling sea water temperature	67.9	77.0
	Condenser train A, tube plugging rate	0	5
2	2nd high pressure feedwater heater train A, tube plugging rate	0	3
	3rd high pressure feedwater heater train A, tube plugging rate	0	3
3	1st reheater train A, tube plugging rate	0	1
	2nd reheater train A, tube plugging rate	0	2
4	Moisture separator train A, efficiency	96.85	96.50

electric output is lower than design electric output, the state of electric output variable is set to 'abnormal'. The inference is based on Bayes' rule as Eq. (9).

$$P(X_i|Y) = \frac{P(Y|X_i)P(X_i)}{P(Y)} \tag{9}$$

where

$P(X_i|Y)$ is the posterior probability of a hypothesis variable after the inference given the evidence of information variable,
$P(X_i)$ is the prior probability of a boundary parameter,
$P(Y|X_i)$ is the conditional probability,
$P(Y)$ is the probability of information variable, and the evidence is given.

Since the actual calculation of Bayes' rule is difficult in case of a large knowledge-base, authors used the inference engine of MSBNx which is mentioned in qualitative modeling.

3. Validation results

The accuracy of Lost MW Calculator was validated by simulated data and actual plant data.

3.1. Test by simulated data

The first validation was achieved by the data simulated by PEPSE. Authors simulated four times more after modifying the boundary parameters as shown in Table 4. In these cases, one or two boundary parameters were modified intentionally. The test cases were selected among the frequent examples of performance degradation occurring in Younggwang NPP. In this validation, because we know root causes, we can identify the diagnosis capability of Lost MW Calculator. After inputting the prior probabilities of the hypothesis variables and the state of information variable generated from the testing data, Lost MW Calculator was executed. The conditional probability

Table 5
Validation results of lost MW calculator

Modified boundary parameters	Test case 1		Test case 2		Test case 3		Test case 4	
	Posterior prob. (%)	Electric loss (MW)	Posterior prob. (%)	Electric loss (MW)	Posterior prob. (%)	Electric loss (MW)	Posterior prob. (%)	Electric loss (MW)
Cooling sea water temp.	100.00	6.31	50.05	0.00	50.05	0.00	50.05	0.00
MS efficiency	68.60	0.00	68.60	0.00	68.61	0.00	69.88	0.47
2nd HP FWH Number of Tubes	50.64	0.00	50.89	0.01	50.64	0.00	50.64	0.00
3rd HP FWH Number of Tubes	50.48	0.00	52.82	0.09	50.48	0.00	50.48	0.00
Condenser Number of Tubes	53.77	0.03	52.98	0.00	52.98	0.00	52.98	0.00
1st RH Number of Tubes	50.12	0.00	50.12	0.00	50.74	0.03	50.12	0.00
2nd RH Number of Tubes	50.24	0.00	50.24	0.00	50.88	0.03	50.24	0.00
Estimated electric output*/Simulated electric output (MW)	–	1047.38/ 1047.62	–	1052.75/ 1053.57	–	1053.67/ 1053.63	–	1053.45/ 1053.29

*Design electric output: 1053.72 MW.

should be fixed since the relation among variables is not changing quantity.

Table 5 shows the validation results. In the upper part of each test case, there is the posterior probabilities and estimated electric loss. In the lower part, there is the comparison result between the estimated electric output and the true electric output from the simulated data. The underlined number represents the modified boundary parameter for each test case. The estimated electric output, $\hat{Y}$ is calculated using Eq. (10).

$$\hat{Y} = Y_{\text{design}} + \sum_{i=0}^{p} \Delta Y_i \tag{10}$$

where Y_{design} is design electric output.

In the test case 1, the estimated electric loss has within ∼4% errors comparing to the simulated case. In other cases which the value of electric loss is comparatively small, that is lower than 0.5 MW, maximum errors are ∼34%. The sensitivity analysis seems to be useful to predict somewhat large degradation, but have still the uncertainty to guess small degradation. This uncertainty depends on the accuracy of PEPSE simulation model as well as regression analysis. In the left column of each test case, there is the diagnosis result using Bayesian network. This posterior probability means the belief for the degradation of a boundary parameter when electric output increases or decreases. We can consider the posterior probability as the degree of assurance for the electric gain or loss. The posterior probability of the modified boundary parameter became higher than that of the boundary parameter with a design value. As the electric loss increases, the posterior probability of a boundary parameter also increases. In test case 3, a little increase of the posterior probability of 'MS efficiency' is because of coupled correlation among reheaters and a moisture separator, which are adjacent components in turbine cycle. 'MS efficiency' has comparatively higher posterior probability than other boundary parameters even if it is normal state. This is because of the characteristic of knowledge-base. Since 'Moisture Separator Efficiency' variable is directly connected to 'Electric Output' variable in Fig. 5, they have strong correlation or less uncertainty on their cause-consequence relation.

3.2. Test by field data

To demonstrate field applicability, the validation using plant data that had been collected in turbine cycle performance tests was accomplished. In Younggwang

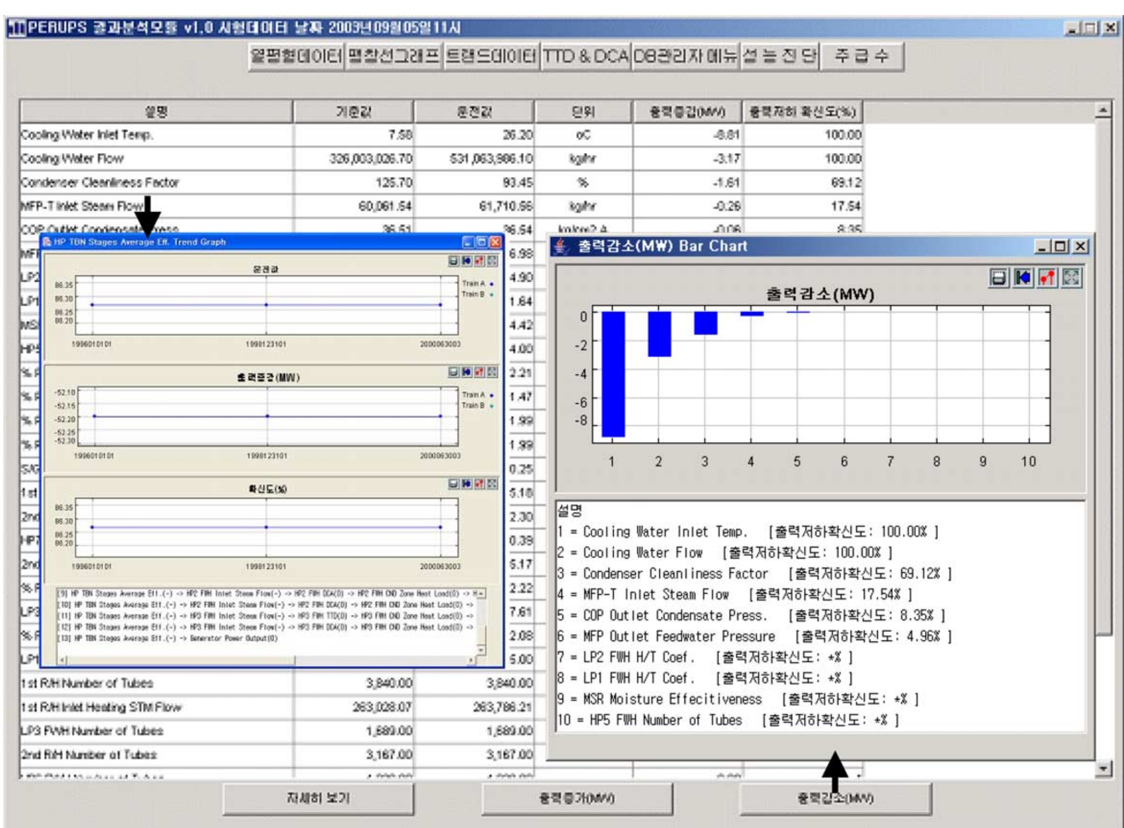

Fig. 6. Graphical user interface of Lost MW Calculator.

NPP units 3 and 4, a full-scale performance test is performed before and after overhaul period, and simplified performance tests are performed every week. We collected the full-scale performance test data and applied them to Lost MW Calculator. Because we do not know the exact root cause in this validation, we only checked the applicability and compared the results and actual maintenance history.

We make a simple graphic user interface displaying the overall results on the web as shown in Fig. 6. In this interface, Korean language and familiar abbreviations are used for the easy understanding to efficiency engineers in power plants. This interface collects the performance test data and executes the Lost MW Calculator. On the interface, users can identify the design and operating value of each boundary parameters including electric output, unit, electric gain or loss, and posterior probability. Using the sub-functions, users observe the trend of the analysis results of a boundary parameter and the rank of electric gain or loss. After the field tests, Lost MW Calculator was installed in Younggwang NPP units 3 and 4.

4. Summary and conclusions

Ultimately, Lost MW Calculator, which is a kind of advisory system for nuclear turbine cycle diagnosis, was developed for the economical performance and maintenance management of NPPs. In the operating NPPs, the reduction of operating cost becomes an important topic to compete other electric power sources. More rapid and more reliable maintenance plays an important role for the reduction of operating cost, because we can diminish the period of shutdown interval. Lost MW Calculator was developed from the viewpoint of industrial application as well as academic purpose. The proposed algorithm can be used for various purposes in plants. Efficiency engineers can identify something trouble using the impact of a component for electric loss and its belief. Also they can do 'what-if' analysis for the behavior of turbine cycle when they need to change some design or operating parameters.

The accuracy of Lost MW Calculator depends on the simulation model and the knowledge-base constructed by Bayesian network. In the future, they will be upgraded continuously with reflecting actual performance test data.

Acknowledgements

This study is carried out as a part of the research project performed by Korea Power Electric Research Institute. We appreciate to Mr Il Heo in Korea Hydro and Nuclear Power Co., Ltd.

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