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Development of a Real-Time Thermal Performance Diagnostic Monitoring System Using Self-Organizing Neural Network for KORI-2 Nuclear Power Unit

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자기학습 신경망을 이용한 원자력발전소 고리 2호기 실시간 열성능 진단 시스템 개발

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Abstract

In this work, a PC-based thermal performance monitoring system is developed for the nuclear power plants. The system performs real-time thermal performance monitoring and diagnosis during plant operation. Specifically, a prototype for the KORI-2 nuclear power unit is developed and exam ined in this work. The analysis and the fault identification of the thermal cycle of a nuclear power plant is very difficult because the system structure is highly complex and the components are very much inter-related. In this study, some major diagnostic performance parameters are selected in order to represent the thermal cycle effectively and to reduce the computing time. The Fuzzy ARTMAP, a self-organizing neural network, is used to recognize the characteristic pattern change of the performance parameters in abnormal situation. By examination, this algorithm is shown to be able to detect abnormality and to identify the fault component or the change of system operation condition successfully. For the convenience of operators, a graphical user interface is also constructed in this work.

요 약

본 논문은 원자력발전소 열성능 감시 시스템의 PC기반 구현에 관한 연구 내용이다. 이 시스템은 열성능 감시와 진단을 플랜트 운전중에 실시간으로 수행할 수 있다. 고리 원전2호기를 목적호기로 원형 시스템을 구성하여 시험해 보았다. 원자력발전소의 열 주기 시스템은 대단히 복잡하고 구성 요소간에 상호 영향이 커서, 그 분석과 고장 진단에 어려움이 많다. 본 연구에서는 열 주기를 효율적으로 표현하고, 계산시간을 단축하기 위해 성능 진단 변수를 설정하였다. 비정상 상태에서의 진단 변수의 특성 패턴 변화를 인식하기 위해 자기학습 신경망의 일종인 퍼지아트맵을 이용하였다. 시험을 통해 이 알고리듬이 비정상 상태를 감지하고 고장 원인을 성공적으로 규명하는 것을 보였으며, 운전원의 편의를 위해 그래픽 사용자 인터페이스를 구축하였다.

1. Introduction

In Korea, the portion of the nuclear power generation is up to 43.2% of the total electric power generation and the average availability of nuclear power plants is 84.5% (1992). It shows that the nuclear power plays a very important role, and the availability is high in comparison with the world average, 69.3% [1]. A major goal of the nuclear power plant operation is to increase the electric output with emphasis on safety, that is, thermal efficiency. In order to achieve this goal, the plant operation should be performed in consideration of both the availability and the thermal efficiency. The effort to improve the nuclear power thermal efficiency seems to be insufficient in comparison with that to improve the availability.

The benefits of using the thermal performance monitoring system are the reduction of derated electric output and the saving of maintenance cost through the early detection of abnormal component. Conventionally, only the component-level performance calculation and analysis have been carried out in the field. In recent years, however, the thermal -cycle-level analysis methods have been developed and the maintenance standard has been established. The next step for the effective thermal performance monitoring is the development of on-line and real-time diagnostic monitoring systems[2]. The conventional performance analysis packages usually contain the huge size software for the simulation of the thermal cycle[3]. It is one of the major reasons why those packages cannot run in real-time. What is worse, additional database (knowledge base) is needed to detect the root cause of the performance change because the thermal cycle is highly complex and the fault component affects the whole thermal cycle parameters.

In this study, a prototype of the diagnostic monitoring system for the thermal performance of the KORI-2 nuclear power unit is established. In this system, some major diagnostic performance parameters are selected and a self-organizing neural network system is used to recognize the abnormal patterns. The major performance parameters are selected in order to represent the thermal cycle. The change of parameters indicates either the abnormality of the thermal cycle component or the change of operation condition. Fuzzy ARTMAP, a self-organizing neural network, is used to recognize the characteristic patterns of the performance parameters in abnormal situations. By training with the diagnosis data, this system is able to detect abnormality and identify the fault component or the change of system operation condition. The training data is produced by FISA-2/WS simulator for KORI-2 nuclear power unit developed in KAIST[4].

2. Selection of Major Diagnostic Performance Parameters in KORI-2 Thermal Cycle

2.1. Description of KORI-2 Thermal Cycle

The BOP (Balance of Plant) of a nuclear power plant contains SGs (steam generators), steam line, turbines, moisture separator, condenser, pumps and heaters. Heat generated by nuclear fission in core is transferred to BOP through SG. Subcooled feed water becomes saturated steam through SGs and transfers its energy to turbine. Exhausted steam from turbine is condensed at the condenser. The BOP system forms the closed loop just as the primary loop. However, it is more complex and it contains two phase flow [4]. In KORI-2 nuclear power unit, the high pressure turbine has two extract lines to the feed water heaters and the low pressure turbine has three. There are five feedwater heaters and one deaerator. There are also three banks of pumps in feed line : One is the bank of main feed pumps, another is the bank of booster feed pumps and the other is the bank of condensate extraction pumps.

Figure 1 shows the conceptual diagram of BOP system in KORI-2 nuclear power unit. It is very hard to present whole phenomena of BOP on a T-s (tem-

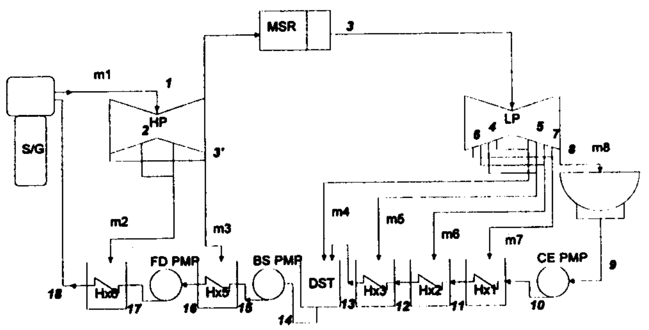

Fig. 1. The Conceptual Diagram of BOP in KORI-2 Nuclear Power Unit

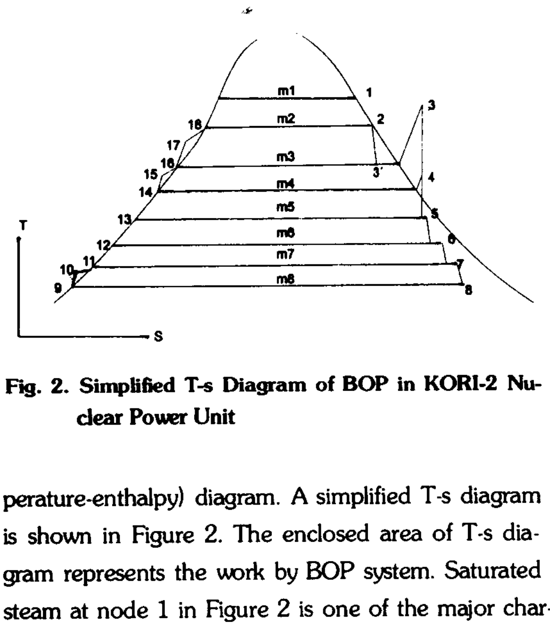

Fig. 2. Simplified T-s Diagram of BOP in KORI-2 Nuclear Power Unit

perature-enthalpy) diagram. A simplified T-s diagram is shown in Figure 2. The enclosed area of T-s diagram represents the work by BOP system. Saturated steam at node 1 in Figure 2 is one of the major characteristics of nuclear power plants.

2.2. Diagnostic Performance Parameters

Heat rate, the ratio of supplied heat to generated electric power, is the representative measure of BOP performance. Equations (1) to (7) show the calculation of heat rate of the KORI-2 nuclear power unit. The parameters related to heat rate are selected as the diagnostic performance parameters.

$$H_R = \frac{\dot{Q}}{\dot{POW}} \tag{1}$$

$$\dot{Q} = m_1(h_1 - h_{18}) + (m_1 - \sum_{i=2}^{3} m_i)(h_3 - h_3') \tag{2}$$

$$\dot{POW} = \eta_{GEN}\,\dot{W}_T \tag{3}$$

$$\dot{W}_T = (\dot{W}_{HP} + \dot{W}_{LP} - \dot{W}_{PMP}) \tag{4}$$

$$\dot{W}_{HP} = m_1(h_1 - h_2) + (m_1 - m_2)(h_2 - h_3') \tag{5}$$

$$\dot{W}_{LP} = \sum_{i=3}^{7}(m_1 - \sum_{j=2}^{i} m_j)(h_i - h_{i+1}) \tag{6}$$

$$\dot{W}_{PMP} = \dot{W}_{FD} + \dot{W}_{BS} + \dot{W}_{CE} \tag{7}$$

In addition to heat rate and its related parameters, TTDs (terminal temperature differences) of various heaters and the condenser pressure are selected in order to obtain the sufficient information for the diagnosis. The turbine work can be replaced by the turbine efficiency[4]. In order to consider the boundary condition of BOP, the SG thermal outputs and the turbine speed are included. The moisture separator efficiency is excluded because measuring the steam quality is not possible in plant operation. Totally 17 performance parameters are selected for the major performance parameters in this study. The selected major parameters represent the BOP status of KORI-2 nuclear power unit. These are as follows:

(1)~(2) Thermal output of steam generator 1 and 2 respectively,
(3) Turbine speed,
(4) High pressure turbine efficiency,
(5) Low pressure turbine efficiency,
(6)~(7) TTDs of reheaters 1 and 2 respectively,

(8) Condenser pressure,

(9)~(13) TTDs of FWHs (feedwater heaters) 1, 2, 3, 5 and 6 respectively,

(14) TTD of deaerator,

(15)~(17) Work of main feed pump, booster feed pump and condensate extraction pump respectively.

2.3. Simple Estimation of Measurement Uncertainty

In order to establish the setpoint for each performance parameter of the monitoring system, the measurement uncertainty must be calculated. In this work, a quite rough estimation is performed because it is nearly impossible to know the accurate uncertainty of whole instrumentation components in BOP system during operation. It is assumed that the statistical uncertainties of BOP instruments are the same as those of safety related instruments and the uncertainty estimation is done one year after calibration. Table 1 shows the uncertainties of the process parameters. The uncertainties of the performance parameters are calculated by Equation (9) as follows[5] :

$$R = fn(P_1, P_2, \ldots P_n) \tag{8}$$

$$U_R = \sqrt{\sum \left(\frac{\partial R}{\partial P_i} U_{P_i}\right)^2} \tag{9}$$

Table 2 shows the estimated uncertainties of the performance parameters which are calculated based on the uncertainty of the process parameters. In this calculation, it is also assumed that the whole process parameters can be measured in the form of temperature, pressure and flow rate and the plant is at the nominal operation condition.

Table 1. The Uncertainty of the Process Parameters

	Reference uncertainty	Drift (12 months)	Uncertainty
Temperature	0.45%	0.33%	0.558%
Pressure	0.25%	0.5%	0.559%
Flowrate	0.92%	0.12%	0.928%

Table 2. The Uncertainty of the Process Parameters

Performance parameter	Estimated uncertainty
Q_{SG}	1.33%
$W_{HP \cdot TBN}$	12.2%
$W_{LP \cdot TBN}$	6.35%
$W_{FD \cdot PMP}$	1.3%
$W_{BS \cdot PMP}$	1.2%
$W_{CE \cdot PMP}$	1.1%
TTDs of FWH	2.55%
P_{CND}	0.558%

3. Self-organizing Neural Network (Fuzzy ARTMAP)

3.1. Architecture of the Fuzzy ARTMAP

The ARTMAP is a neural network algorithm by which training can be done in supervised learning mode. Figure 3 shows the algorithm of the Fuzzy ARTMAP. W^a, W^b and W^{ab} are the weight matrices. X^a, X^b and Xab are the output vectors of modules. A is the input vector and B is the expected output vector. The ARTMAP consists of two ART modules and a map field. The map field controls the weight vector to meet the recognition criteria. A pair of ART modules (ART_a and ART_b) are capable of self-organizing stable recognition categories in response to arbitrary sequences of input patterns. The ARTMAP autonomously learns to classify arbitrarily many, arbitrarily

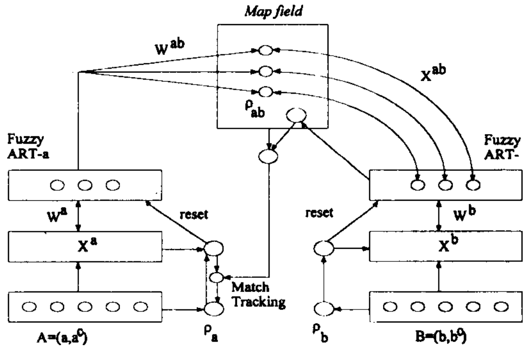

Fig. 3. Algorithm of Fuzzy ARTMAP

ordered input vectors into recognition categories[6][7][8][9]. The mismatch increases the vigilance parameter ρ_a, of ART_a by the minimal amount needed to correct the mismatch at ART_b. Search occurs if the degree of match is less than ρ_a, the ARTMAP is hereby a type of self-organizing expert system that calibrates its selectivity. Between input trials, ρ_a relaxes to a baseline vigilance ρ_a^{base}. When ρ_a^{base} is large, the system runs in a conservative mode, wherein predictions are made only if the system is confident of the outcome [10][11]. Where ART 1 dynamics are described in terms of set-theoretic operations, Fuzzy ART dynamics are described in terms of fuzzy set-theoretic operations.

The Fuzzy ARTMAP provides more general use of the ARTMAP system that learns to classify analog as well as binary vectors. This generalization is accomplished by replacing the ART 1 modules of the binary ARTMAP system with the Fuzzy ART modules.

3.2. The Diagnostic Monitoring System of the Thermal Performance Using the Fuzzy ARTMAP

The Fuzzy ARTMAP has many merits to be used in the monitoring system. Especially, the self training function of the Fuzzy ARTMAP can update its database in adaptive manner by using at real plant. A key to use the Fuzzy ARTMAP as a diagnostic monitoring system is how to keep the balance between the accuracy and the continuity. The degree of the discreteness in recognition is governed by the vigilance parameter ρ_a^{base}, so ρ_a^{base} must be well tuned to use the Fuzzy ARTMAP, a competition neural network. The monitoring system must be able to distinguish each abnormal patterns of performance parameters from others. It also must be able to recognize similar abnormality for the same. When subtle differences of similar abnormality are detected, the knowledge base of the monitoring system becomes unpractically large.

3.3. Results of Applying Algorithm

For the examination of monitoring algorithm, 5 data sets were used for training and 4 noisy data sets were used for test. For the training data sets, selected BOP conditions were normal condition, highly and slightly increased condenser pressure conditions respectively and the steam line break condition at full power operation. The turbine load change condition is selected to represent the change of the power level. Training data sets were obtained from FISA-2/WS micro simulator which was developed in KAIST[4]. Noisy data sets for testing were arbitrarily generated within the estimated uncertainty of performance parameters. The vigilance parameter of the Fuzzy ARTMAP, ρ_a^{base}, was tuned to 0.95. Table 3 shows the training data sets and assigned outputs. Assigned values are used in order to identify the training data sets. Test data sets and their results are also shown in Table 3. The expected test results are the assigned output values which have been trained for each selected case. As can be seen in Table 3, the algorithm successfully distinguished 5 individual data sets. It also made adequate decisions for the noisy data inputs.

4. Prototype of Monitoring System Including Man Machine Interface (MMI) System

For the convenient use of this diagnostic monitoring system, MMI is designed. The graphical user interface method is applied. Figure 4 shows the demonstration screen of developed MMI system. Performance parameters are displayed in the left side of the window. In normal performance condition, historic thermal performance problems are displayed and the background color of the window is white. Background color varies along the thermal performance and the root cause of abnormality is displayed in right side. When the pattern of parameters is absolutely a newcomer, i.e., it has not been trained, this monitoring system is still able to detect the problem, but

Table 3. The Training Data Sets and Assigned Outputs (left half) and Test Data Sets and Their Results (right half)

	Training					Test			
Para #	Normal	Cond. pr. increased slightly	Cond. pr. increased highly	SL break	Turbine load change	Noisy normal	Noisy cond. Pr. inc.	Noisy SL break	Noisy TBN load change
(1)	943091.8	943091.8	943091.8	943091.8	848782.6	950191.8	943091.8	943091.8	848782.6
(2)	943091.8	943091.8	943091.8	943091.8	848782.6	943091.8	943091.8	943091.8	848782.6
(3)	1800.0	1800.0	1800.0	1800.0	1800.8	1801.0	1810.0	1800.0	1800.8
(4)	0.828	0.828	0.828	0.828	0.828	0.818	0.828	0.828	0.828
(5)	0.726	0.726	0.726	0.726	0.726	0.726	0.700	0.756	0.726
(6)	5.090	5.090	5.090	5.090	3.796	5.100	5.000	5.090	3.796
(7)	11.70	11.70	11.70	11.70	11.23	12.00	11.70	11.60	11.23
(8)	4.75e-03	3.36e-02	7.36e-02	4.75e-03	4.55e-03	4.75e-03	2.86e-02	4.75e-03	4.55e-03
(9)	8.165	8.165	8.165	8.165	7.323	8.265	8.165	8.165	7.323
(10)	16.91	16.91	16.91	16.91	16.62	16.91	16.91	17.51	15.72
(11)	28.90	28.90	28.90	28.90	28.94	28.90	25.90	29.42	28.94
(12)	33.26	33.26	33.26	33.26	32.55	34.26	33.26	33.26	32.55
(13)	22.20	22.20	22.20	22.20	21.29	22.90	22.20	22.20	21.29
(14)	145.7	145.7	145.7	145.7	142.7	145.0	147.7	145.7	141.7
(15)	8372.72	8389.8	8412.4	8807.1	8230.1	8422.72	8389.8	8600.1	8330.1
(16)	4368.91	4377.8	4389.6	4595.6	4294.5	4368.91	4377.8	4595.6	4294.5
(17)	3103.54	3120.0	3141.7	3391.6	3179.9	3153.54	3125.0	3391.6	3179.9
Assigned Output (Result)	0.0	1.0	2.0	3.0	4.0	0.0	1.0	3.0	4.0

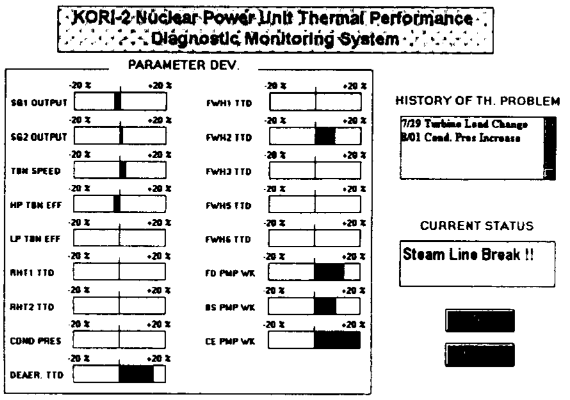

Fig. 4. The Demonstration Screen of Developed MMI System

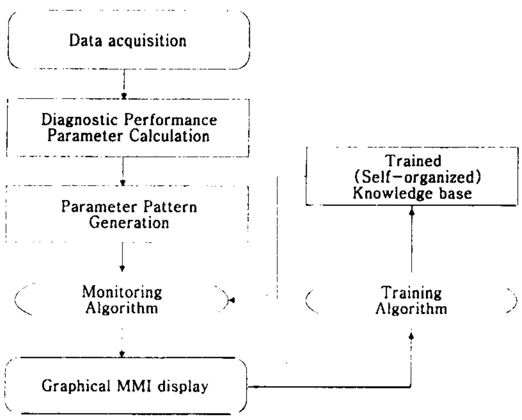

Fig. 5. The Schematic Diagram of the Developed Monitoring System

can not identify the root cause. It will ask the engineer or operator what the problem is. When it takes the answer from the engineer, it can automatically enlarge its knowledge base on this abnormality.

Figure 5 shows the schematic diagram of the developed monitoring system. It consists of data acquisition, parameter calculation, pattern generation, monitoring algorithm, knowledge base, training algorithm and MMI display. Training algorithm works when the operator requests to generate a new pattern or when the input pattern is not familiar to the monitoring system.

5. Conclusions

A diagnostic monitoring system for the thermal performance improvement using the Fuzzy ARTMAP algorithm and the graphical user interface was developed in this work. Specifically, the prototype for KORI-2 nuclear power unit was developed and examined. It is believed that the thermal efficiency and the convenience of nuclear power plant operation can be improved by using this monitoring system since it provides operators with continuous information on the current thermal performance as well as the historic data through the graphical MMI.

In this work, we used the data from the FISA-2/WS micro simulator to establish the database of the monitoring system which is one of the most critical parts of the system. As we improve the database by using more accurate simulator and as we select more number of performance parameters monitored in the future work, we expect we can establish the better monitoring system.

Nomenclature and abbreviation

H_R	Heat rate
$\dot{Q}$	Supplied heat to the BOP from the primary loop through SGs
$P\dot{O}W$	Generated electric output
$\dot{W}_T$	Net output work of the turbine
$\dot{W}_{HP}$	Work of the high pressure turbine
$\dot{W}_{LP}$	Work of the low pressure turbine
$\dot{W}_{PMP}$	Total work of the pumps
$\dot{W}_{FD}$	Work of the main feed pump
$\dot{W}_{BS}$	Work of the booster feed pump
$\dot{W}_{CE}$	Work of the condensate extraction pump
$m_1 \sim m_8$	Mass flow rates shown in Figure 1 and Figure 2
$h_1 \sim h_{18}$	Enthalpies of nodes shown in Figure 1 and Figure 2
U_R	The uncertainty of the calculated parameter, R
U_{Pi}	The uncertainty of the measured parameter, P_i
BOP	Balance of plant
SG	Steam generator
FWH	Feedwater heater
TTD	Terminal temperature difference
MMI	man machine interface

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