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Diagnosis of feedwater heater performance degradation using fuzzy inference system

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ABSTRACT

Power generation facilities cannot avoid performance degradation caused by severe operating conditions such as high temperature and high pressure, as well as the aging of facilities. Since the performance degradation of facilities can inflict economic on power generation plants, a systematic method is required to accurately diagnose the conditions of the facilities.

This paper introduces the fuzzy inference system, which applies fuzzy theory in order to diagnose performance degradation in feedwater heaters among power generation facilities. The reason for selecting only feedwater heaters as the object of analysis is that it plays an important role in the performance degradation of power generation plants, which have recently been reported with failures. In addition, feedwater heaters have the advantage of using many data types that can be used in fuzzy inference because of low measurement limits compared to other facilities. Fuzzy inference systems consists of fuzzy sets and rules with linguistic variables based on expert knowledge, experience and simulation results to efficiently handle various uncertainties of the target facility. We proposed a method for establishing a more elaborate system. According to the experimental results, inference can be made with consideration on uncertainties by quantifying the target based on fuzzy theory. Based on this study, implementation of a fuzzy inference system for diagnosis of feedwater heater performance degradation is expected to contribute to the efficient management of power generation plants.

1. Introduction

Performance degradation refers to a phenomenon in which a device fails to exhibit its intended performance. Power generation facilities, such as Nuclear Power Plants (NPPs), operated under severe conditions of high temperature and high pressure for long periods cannot avoid performance degradation. In fact, such issues have been frequently reported with the recent aging of facilities. As the performance degradation of facilities lead to economic, it is necessary to maintain and repair facilities based on accurate diagnosis before such serious conditions occur.

A feedwater heater is a device that preheats water supplied to a steam generator to maintain appropriate temperature conditions, and has the advantages of improving the cycle efficiency, minimizing the thermal stress of the steam generator, and preventing the reduction of life. When performance degradation occurs in such a facility, the heat transfer capacity of the feedwater channel is reduced to directly affect generation efficiency.

Through the past research, we developed a methodology using a regression model (Jee, Heo, Jang, & Lee, 2011) and a methodology using diagnosis tables (Kim & Heo, 2012) to diagnose the thermal performance degradation in feedwater heaters. The methodology using the regression model is a numerical analysis method that expresses the performance degradation of the facility and the performance degradation caused by surrounding facilities as mathematical formulae and computes the results through matrix calculations corresponding to the number of facilities. Reliability of this methodology was reduced when noise occurred in the data measured at the actual site, and there was difficulty in uniform application of the methodology to power generation plants operating under different conditions. The methodology using diagnosis tables is widely used at the actual sites because it can make an inference about the type of performance degradation present based on fluctuation of the data. Nonetheless, this methodology cannot make an inference about the severity of performance degradation that is found. The purpose of this study is to apply fuzzy logic as a method to make up for the shortcomings of these prior stud-

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ies (Kothamasu & Huang, 2007; Wang & Hu, 2006; Wang & Elhag, 2008).

The body of this paper introduces a simulation of the performance degradation using simulation software, preparation of a diagnosis table using data obtained from the simulation, and a diagnosis using a fuzzy inference system.

There are different types of fuzzy inference methods, and the Mamdani fuzzy inference method is the most widely used method of direct inference. The advantage of the Mamdani fuzzy inference method using an If-Then rule is that it first determines whether an appropriate control input value of the user belongs to the membership function using 'If' and then converts the value into a number by calculating the degree to which the value belongs to the fuzzy set using 'Then'. This inference method can make use of qualitative advantages of the methodology using a diagnosis table because it prioritizes fluctuation of the variables. Further, because it is a simple operation, the instability of the numerical analysis used in the regression model can be improved. Detailed inference and operation processes will be introduced in the following section (Abraham, 2005).

In this paper, the feedwater heaters of NPPs were selected as the objects of study. When performance degradation occurs in a feedwater heater, its measurement values fluctuate. Here, while degradation of thermal performance identically occurs on the macroscopic level, internal phenomena differ in each case and show different trends in the fluctuation of the variables. This study intends to make an inference about the type and degree of performance degradation using the fluctuation of measurement values (Guimara & Lapa, 2007). First of all, the limited condition described below is taken into account for simplification of the design of the performance degradation detection system. 1) Among the diverse performance degradations that may occur in a feedwater heater, five representative single performance degradation phenomena are used, including excessive increase in drain water level due to malfunctioning of the drain valve or from other causes, reduced pressure of the heater shell due to alien substances, clogging of the tube, phenomenon in which the feedwater does not pass by the heating part due to a defect in the pass partition plate, and leakage in the feedwater tube. 2) Double performance degradation phenomena assume cases in which two of the phenomena mentioned above overlap. An assumption was made that performance degradation phenomena occur sequentially instead of simultaneously. Therefore, triple performance degradation is not considered, as it is possible to detect it before the overlapping of three phenomena (Hadjimichael, 2009).

2. Mamdani fuzzy inference method

A fuzzy inference system (FIS) is based on fuzzy set theory, fuzzy rules, and fuzzy reasoning. It is widely applied to automatic control, robotics, pattern recognition, time series prediction, and fault diagnosis (Guillaume, 2001).

Fuzzy inference based on fuzzy reasoning is more similar to human thinking and natural language compared to existing reasoning systems, and it can be effectively used to describe approximate and uncertain phenomena in the real world. The core part of an FIS consists of a diagnostic rule with a series of linguistic forms, which includes fuzzy association. The inference result is generated by a fuzzy compositional rule. In the end, FIS performs the shifts the role of the inference rule created by experts based on inference knowledge into the role of machine. In general, FISs show outstanding results compared to existing systems when the system cannot be interpreted by existing quantitative methods due to complexity or if the obtained information is qualitative, inaccurate and uncertain. Zadeh (1965), who defined fuzzy logic, presents the 'principle of incongruity' as the reason for these results. This principle states that when a system has a certain degree of complexity, it becomes impossible to provide an accurate and meaningful description of the behavior of the system using a quantitative method. In this case, a qualitative method that sacrifices quantitative relationships is a desirable and useful model.

The authors paid attention to the strengths of the Mamdani model rather than the strengths of the TSK (Takagi–Sugeno–Kang) model, which is quick and effective in terms of calculation. Mamdani model can return output values that can intuitively express expertise, which helps operators of power plants to understand the state of a feedwater heater intuitively.

2.1. Fuzzy sets

Fuzzy sets expand an existing set using the concept of fuzzy logic, and each element has a degree to which it belongs to the set (degree of membership). Here, the degree of membership is expressed as a real number between 0 and 1, where the case in which an element completely belongs to the set is 1 and the case in which it does not belong to the set is 0. This can be expressed using Eq. (1):

$$\mathrm{A} = \{(\mathrm{x}, \mu_A(\mathrm{x}))|\mathrm{x} \in \mathrm{X}\},\ \ 0 \le \mu_A(\mathrm{x}) \le 1. \tag{1}$$

$\mu_A(x)$ is referred to as the membership function (MF) of the fuzzy set A, and the membership function plays the role of the corresponding elements of the universal set X for each value of the membership function.

The fuzzy set A can be briefly expressed as below; specifically, it is expressed as Eq. (2) if the elements of the universal set □ are continuous and as Eq. (3) if they are discontinuous.

$$\mathrm{A} = \int \mu_A(x)/x, \tag{2}$$

$$\mathrm{A} = \sum_{x_i \in X} \mu_A(x_i)/x_i. \tag{3}$$

2.2. Fuzzy rules

Knowledge base of the fuzzy inference system consists of a database and a rule. A fuzzy rule is expressed as a linguistic rule in the form of 'If-Then'. This rule has the fuzzy conditional statements as shown in Eqs. (4)–(6) below.

$$R_1 : If\ x\ is\ A_1\ and\ y\ is\ B_1\ then\ z\ is\ C_1, \tag{4}$$

$$R_2 : If\ x\ is\ A_2\ and\ y\ is\ B_2\ then\ z\ is\ C_2, \tag{5}$$

$$R_n : If\ x\ is\ A_n\ and\ y\ is\ B_n\ then\ z\ is\ C_n, \tag{6}$$

Here, x, y and z represent state variables and inference input variables of the system used as the input information of the inference system, and A_i, B_i and C_i refer to the fuzzy values (fuzzy sets) of x, y and z defined for the universal sets U, V and W, respectively. In addition, individual conditional statements can be represented by fuzzy relations called R_i, and they are gathered to form a set of rules (Liu, Yang, Wang, Sii, & Wang, 2004; Takagi & Sugeno, 1985).

2.3. Fuzzy inference process

The inference process of the fuzzy system used in this study is as shown in Figs. 1 and 2. For convenience in calculation and indication, triangular and trapezoidal fuzzy membership functions were used.

Fig. 1 shows fuzzy sets and fuzzy rules for the inference. The first two fuzzy sets correspond to the input part of the variables.

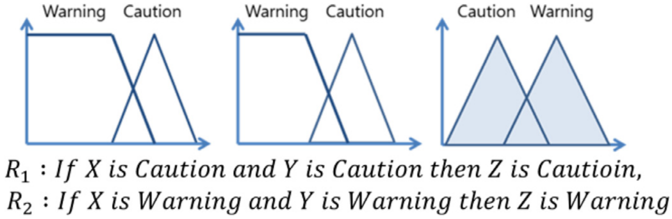

Fig. 1. Schematic diagram of the membership function and rules.

Reduction in the variable was indicated as Caution to an appropriate level, and the remaining values were indicated as Warning. The last fuzzy set is the conclusion, which shows the resulting values of the input part. As for the input part, it consisted of two fuzzy sets. Diverse results can be presented by elaborating this part.

First, the degree of membership of a fuzzy set that constitutes each rule is determined by the given inputs (Input 1, Input 2). Next, the result of inference for each rule is found using the degree of membership. The 'and' operation was used here, which takes the minimum value of each fuzzy set. The inference result is deduced by the integration and defuzzification of rules coming out as the outputs. Eq. (7), a widely used centroid method, was used for defuzzification.

$$\text{Center of gravity} = \frac{\int_a^b \mu_A(x) x dx}{\int_a^b \mu_A(x) dx}. \tag{7}$$

3. Degradation simulation

Performance degradation of the feedwater heaters in NPPs must be simulated for this study. Simulation software, called PEPSE (Performance Evaluation of Power System Efficiencies) which was developed by ScienTech, was used. PEPSE is a generic-purpose simulation toolbox for steam or gas turbine cycles, and widely used for performance analysis in industry and research sectors (Alder, Blakeley, Fleming, Kettenacker, & Minner, 1996).

As the object of study, 1000 MWe model and 1400 MWe model were selected to increase applicability since more than 2/3 operating NPPs belongs to this type. The configuration of the model is based on the simplified piping and instrumentation diagram of the turbine cycle. In this study, we refer to this model as a 'base model.' The accuracy of the base model was validated by comparing the results produced by the base model with the design heat balance diagrams for valve wide open (VWO), 100%, and 75% electric output, which were provided by the turbine vendor (Heo & Lee, 2012). Representative performance degradation phenomena of the feedwater heater were selected through a literature review, and modeling was done to create a simulation as close as possible to the actual phenomena. This process was used to test whether the simulation results were similar to the symptoms of degradation explained in previous studies as well as to use the results as learning data for the fuzzy inference system.

3.1. Degradation modeling

The feedwater heater is one of the core devices at power generation plants in charge of regeneration cycle. As it is difficult to visually confirm problems in a feedwater heater, parameters, such as pressure of the shell or tube, entry and exit temperature of the feedwater, and temperature of the drain condensate, must be reviewed to resolve the problems. Terminal temperature difference (TTD), drain cooler approach (DCA), tube temperature difference, and shell temperature difference can be easily found using tag data obtained at the power plants, and the problem of thermal transfer can also be resolved. Tag data is therefore used as diagnostic data. In general, the interior of the feedwater heater is divided into three zones, such as the De-superheating Zone, Condensing Zone, and Drain Cooling Zone. Depending on the conditions, not all feedwater heaters will have all of these zones present. Fig. 2 is the schematic diagram of a two-zone feedwater heater divided into a Condensing Zone and a Drain Cooling Zone, which is used mainly in nuclear power plants. This feedwater heater is a shell-tube type and shows heat exchange without mixing the fluid from each part.

TTD and DCA are commonly used as performance indicators of the feedwater heater (Fig. 3). TTD is the difference between the saturation temperature of vapor pressure inside the feedwater heater and the temperature of the feedwater at the tube exit. DCA is the difference between the drain temperature of steam extrac-

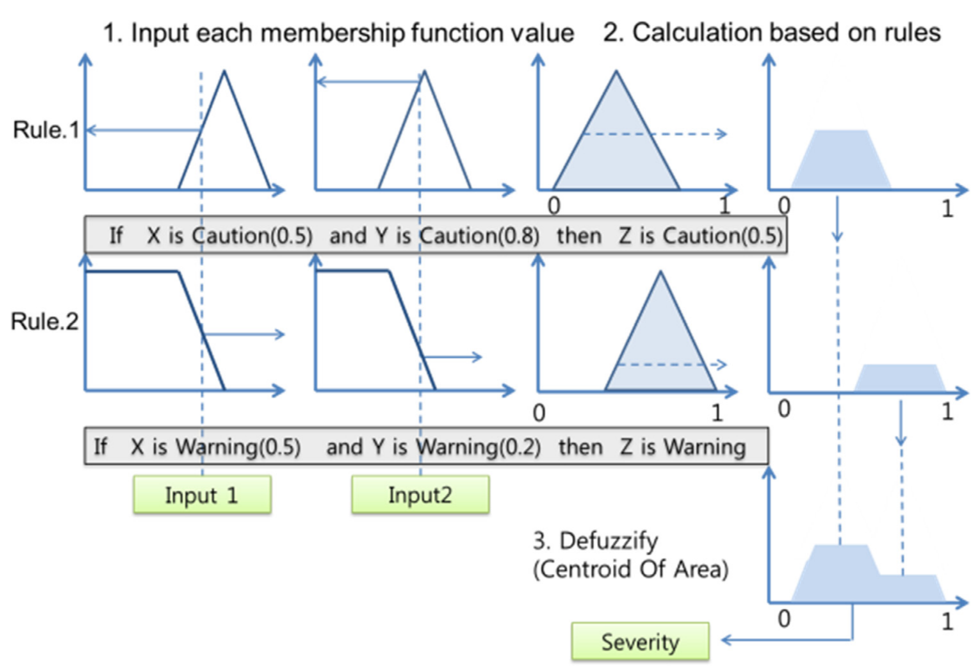

Fig. 2. Schematic diagram of fuzzy logic processes.

Table 1
Degradation mode and related cause and consequence.

Degradation	Cause	Consequence
High Drain Level (HDL)	Tube flooded due to over-condensing or tube leakage	Effective heat transfer area decreases
Low Shell Pressure (LSP)	Over-condensing, shell leakage, or leakage at venting valve	Constraint between turbine and feedwater heater
Tube Pressure Increase (TPI)	After tube plugging, pressure increases in the tube	Pressure drop increased in tube
Pass Partition Plate Leakage (PPPL)	Integrity of material under high pressure	By pass heat transfer zone in feedwater heater
Tube Leakage (TL)	Integrity of material under high pressure	Feedwater flow decreases

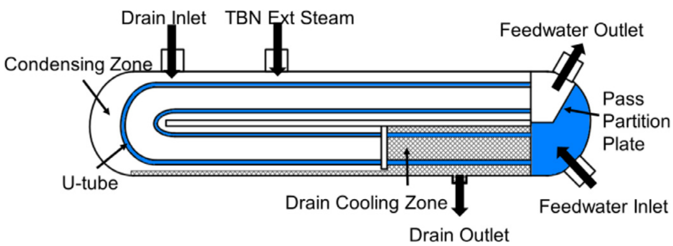

Fig. 3. Schematic diagram of a feedwater heater (two-zone, Shell-Tube type) in NPP.

tion and the temperature at the entrance of the tube. Additional indicators used in this study include the temperature difference at the entrance and exit of the tube, the temperature difference at the entrance and exit of shell, and the pressure reduction in the tube. Eq. (8) shows the equations for these indicators.

$$\begin{aligned} TTD &= T_{SAT}(Shell\ inlet) - T(Tube\ outlet) \\ DCA &= T(Shell\ outlet) - T(Tube\ inlet) \\ \Delta T_{tube} &= T(Tube\ outlet) - T(Tube\ inlet) \\ \Delta T_{shell} &= T(Shell\ outlet) - T(Shell\ inlet) \\ \Delta P_{tube} &= P(Tube\ outlet) - P(Tube\ inlet) \end{aligned} \tag{8}$$

In this paper, 15 performance degradation modes of the feedwater heater were considered, which includes 5 single modes and 10 double modes that combine two single modes. Table 1 explains the cause and consequence of the single degradation phenomenon, and double modes are phenomena in which two single modes are overlapped.

3.2. Data production

PEPSE simulations can be used to illustrate performance degradation phenomena similar to real world situations and obtain results. The ultimate goal of this study is to find the cause of a given consequence.

Simulation of each performance degradation was continued until the output of the power plant was reduced by 0.1%. This means that for a power plant with an output of 1000 MWe, an output reduction of about 1 MWe results from performance degradation. Considering the fact that output is reduced by about 0.7–0.8% when a feedwater heater is not operated (by-pass), this value is appropriate as the threshold of output reduction caused by performance degradation.

3.3. Diagnosis table

A diagnosis table can be prepared using the results of the sensitivity analysis. After summarizing the amount of change in each variable, performance degradation can be inferred by observing the degree of fluctuation of each variable until the threshold of the simulation set forth by the user is reached. Table 2 shows qualitative and quantitative diagnostic tables; colored boxes indicate an increase and non-colored boxes indicate a decrease in the variable. Changes of the variables were normalized according to Eq. (9). These values are used to compose the fuzzy inference system, and the amount of change determines the range of the fuzzy set. When constituting a fuzzy inference system, using the amount of change in the variables will rely on data from the specific power. Therefore, each variable needs to be normalized for application, regardless of the power plant model.

$$X_{normalized} = \frac{X_{operation} - X_{design}}{X_{design}}. \tag{9}$$

A reason for which normalization was required was that this study attempted to apply the same FIS to other power plants. As the operation conditions differ among power plants, then if raw values that have not been normalized are used, FIS will be applied only to the power plants that were used for modeling. As mentioned in Section 3.2, all performance degradation simulations were performed to a point that power plant output decreased to 0.1%. Values that raw values which were obtained at the time were normalized were those shown in Table 2. Here, the values given are the relative variation, not the absolute variation. In Table 2, positive values indicate that the variables will increase when degradation occurs, while negative values indicate they will decrease. As shown in Eq. (9), the size of the values is an indicator that shows how sharply the values change when they increase or decrease relative to one another.

First, as it considers both single and double degradation modes, it can infer more diverse degradation phenomena. In addition, existing diagnosis tables made inferences by observing the fluctuations of two to three representative variables for each phenomenon. On the contrary, current research can perform precise inference by observing variables with small fluctuations. Unlike the method of inference that only considers variables with large changes, information about unchanging variables can also be reflected using a fuzzy inference system. Last, different consequences can be inferred and classified according to the number of variables measured. This study proposed an inference method using seven variables, which requires eight sensors. However, it cannot be assured that actual power plants require all sensors. Regarding this problem, the range of inference according to the measurement limits must be taken into account. In the current diagnosis table, 'TPI' and 'LSP + TPI' can be differentiated by their different trends of change. When shell inlet pressure cannot be measured, these two variables cannot be distinguished because their trend of change becomes identical. The sub-optimal advantage of an FIS is that phenomena that do not appear as inference results can be excluded from analysis when the two variables cannot be distinguished from each other due to identical change. In addition, phenomena that cannot be distinguished using the variables considered in this study can be examined by adding more variables.

3.4. Experiments using the fuzzy inference system

This section examines the process of the fuzzy inference system proposed in this study.

The first step is to establish an expert system. This is the step in which the input and output variables and their ranges are determined. Data obtained from the simulation correspond to this step.

Table 2
Diagnosis table of single and double degradation.

Degradation	Parameter TTD	DCA	ΔT_{tube}	ΔT_{shell}	ΔP_{tube}	Shell inlet pressure	Shell inlet flowrate
Single degradation mode							
① HDL	+2.74	−0.49	−0.24	+0.08	−0.02	+0.01	−0.18
② LSP	−0.23	−0.36	−0.23	−0.21	−0.02	−0.12	−0.17
③ TPI	+2.47	+0.73	−0.22	−0.10	+2.85	+0.01	−0.15
④ PPPL	+2.56	−0.07	−0.22	+0.02	−0.45	+0.01	−0.17
⑤ TL	−0.08	+0.34	+0.01	−0.05	−0.07	+0.01	−0.01
Complex degradation mode							
⑥ HDL + LSP	+1.52	−0.61	−0.38	−0.17	−0.03	−0.11	−0.28
⑦ HDL+TPI	+2.47	−0.45	−0.21	+0.07	+0.83	+0.01	−0.16
⑧ HDL+PPPL	+2.48	−0.48	−0.21	+0.07	−0.33	+0.01	−0.16
⑨ HDL+TL	−0.08	−0.19	+0.09	+0.11	−0.59	+0.01	−0.22
⑩ LSP+TPI	+0.83	+0.04	−0.22	−0.16	+1.00	−0.07	−0.16
⑪ LSP+PPPL	+1.20	−0.22	−0.23	−0.10	−0.29	−0.17	−0.16
⑫ LSP+TL	−0.11	+0.39	+0.01	−0.05	−0.08	+0.01	−0.01
⑬ TPI+PPPL	+2.65	+0.29	−0.23	−0.04	+0.28	+0.01	−0.17
⑭ TPI+TL	+0.32	+0.29	−0.02	−0.04	+0.28	+0.01	−0.08
⑮ PPPL+TL	−0.23	+0.39	+0.03	−0.05	−0.16	+0.01	−0.03

Table 3
Mark of linguistic values and ranges.

Linguistic values	Mark	Normalization range
Caution	C	0–65%
Warning	W	35–100%

Table 4
Parameter and membership range – HDL.

Parameter	Normalization value	Fuzzy membership range C, W
TTD	+2.74	[0, 1.781], [0.959, 2.740]
DCA	−0.49	[−0.319, 0], [−0.490, −0.172]
ΔT_{tube}	−0.24	[−0.156, 0], [−0.240, −0.084]
ΔT_{shell}	+0.08	[0, 0.052], [0.028, 0.080]
ΔP_{tube}	−0.02	[−0.013, 0], [−0.020, −0.007]
Shell inlet pressure	+0.01	[0, 0.007], [0.004, 0.010]
Shell inlet flow rate	−0.18	[−0.117, 0], [−0.180, −0.063]

In this study, seven variables (TTD, DCA, ΔT_{tube}, ΔT_{shell}, ΔP_{tube} shell inlet pressure, shell inlet flow rate) were selected.

The variables above have the same effect on the diagnosis of each performance degradation, and values closer to the maximum change shown in the diagnosis table of Table 2 can be seen to have a greater effect. For instance, when a performance degradation called ‘High Drain Level’ occurs and the changed TTD value is normalized, it would contribute more to the resulting value as it approaches 2.74.

Fuzzy sets have different forms, but triangles and trapezoids are widely used because of their ability to express expert knowledge and simplify the calculation process. In this study, triangular fuzzy sets were used for parts with a defined range and trapezoidal sets were used for parts with an undefined range. Table 3 below shows the ranges of the fuzzy sets for each variable used in this study. Table 3 is referred to calculate *x_design* as well as *x_operation* in Eq. (9). This paper presents a method that sets the output value using only two fuzzy sets such as ‘Caution (C)’ and ‘Warning (W)’ but it can be subdivided more depending on the service environment. As an example, Table 4 shows the normalization range for variables when the performance degradation ‘High Drain Level’ occurs. If the design value for parameters is used in Table 4, the normalization range corresponds to *x_design*. In the same manner, if the operation condition is used, the normalization range becomes x_operation.

Figs. 4 and 5 show the fuzzy sets for the variables TTD and DCA when ‘High Drain Level’ occurs. When this degradation occurs, TTD is increased and DCA is decreased. When the normalization range is exceeded, the degree of membership for the ‘Warning (W)’ set is set to 1 so that inference can continue to result in ‘Warning’. This method is applied to different degradation phenomena and their variables. Fig. 6 shows the fuzzy set that corresponds to the infer-

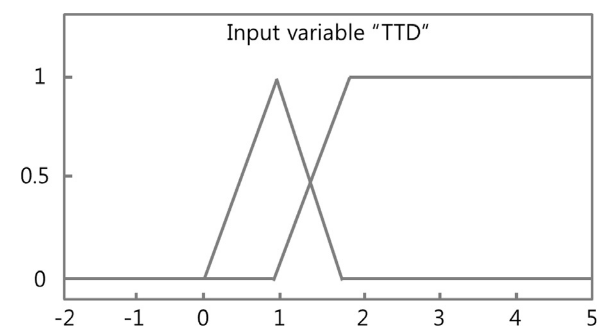

Fig. 4. Membership function of High Drain Level: TTD.

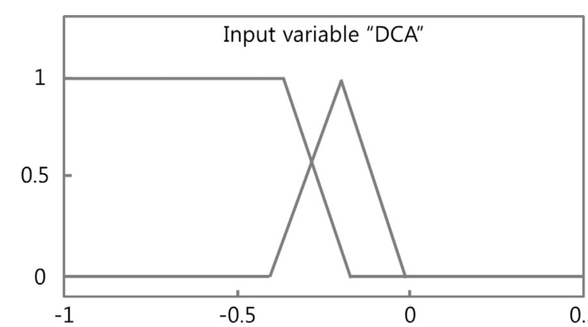

Fig. 5. Membership function of High Drain Level: DCA.

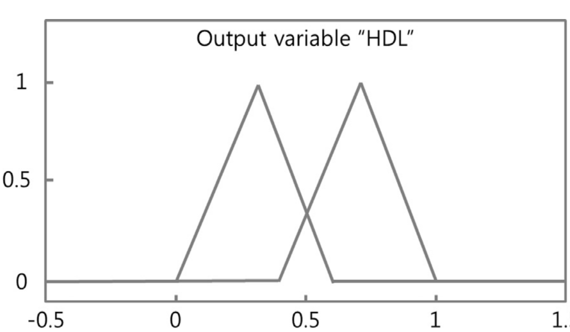

Fig. 6. Result membership function of High Drain Level.

Table 5
Rule of fuzzy inference system.

No.	TTD	DCA	ΔT_{tube}	ΔT_{shell}	ΔP_{tube}	Shell inlet pressure	Shell inlet flow rate	Result
1	C	C	C	C	C	C	C	C
2	C	C	C	C	C	C	W	C
3	C	C	C	C	C	W	C	C
⋮								
126	W	W	W	W	W	C	W	W
127	W	W	W	W	W	W	C	W
128	W	W	W	W	W	W	W	W

Table 6
Results of fuzzy inference: single degradation.

Degradation	Simulation		Fuzzy inference result		RMSE
	Degree	Linguistic value	Degree	Linguistic value	
HDL	33.0%	C	40.7%	C	6.99
	56.0%	W	65.0%	W	
	70.0%	W	67.5%	W	
LSP	25.0%	C	32.5%	C	4.57
	55.0%	W	54.7%	W	
	65.0%	W	67.5%	W	
TPI	32.0%	C	32.5%	C	11.67
	66.0%	W	55.9%	W	
	85.0%	W	67.5%	W	
PPPL	20.0%	C	32.5%	C	8.37
	52.0%	W	57.8%	W	
	72.0%	W	67.5%	W	
TL	17.0%	C	32.5%	C	11.48
	46.0%	C	58.2%	W	
	65.0%	W	67.5%	W	
HDL + LSP	20.0%	C	32.6%	C	8.02
	60.0%	W	54.7%	W	
	70.0%	W	67.5%	W	
HDL + TPI	15.0%	C	32.5%	C	16.96
	40.0%	C	57.8%	W	
	52.0%	W	67.5%	W	
HDL + PPPL	26.0%	C	50.0%	C or W	18.92
	56.0%	W	50.0%	C or W	
	88.0%	W	66.5%	W	
HDL + TL	15.0%	C	32.5%	C	18.36
	54.0%	W	52.5%	W	
	94.0%	W	67.5%	W	
LSP + TPI	35.0%	C	33.9%	C	3.30
	53.0%	W	54.1%	W	
	73.0%	W	67.5%	W	
LSP + PPPL	40.0%	C	32.5%	C	17.52
	60.0%	W	45.2%	C	
	80.0%	W	54.6%	W	
LSP + TL	26.0%	C	32.5%	C	5.62
	40.0%	C	46.8%	C	
	70.0%	W	67.5%	W	
TPI + PPPL	40.0%	C	32.5%	C	17.81
	63.0%	W	40.3%	C	
	87.0%	W	67.5%	W	
TPI + TL	34.0%	C	32.6%	C	6.69
	45.0%	C	45.4%	C	
	72.0%	W	60.5%	W	
PPPL + TL	13.0%	C	50.5%	W	28.63
	39.0%	C	67.5%	W	
	52.0%	W	67.5%	W	

ence result. Two inference results will appear because the set consists of two functions. The functions used here can be diversified to further segment the inference result, appropriately connecting them with the fuzzy rules. This same method was used on 15 performance degradation phenomena and seven variables, but only a few of them are presented in this paper due to space limitations.

The final inference is performed as all measurement values are entered into condition by finding the degree of membership for each fuzzy set. For example, the final inference value of 0.325 implies that the fuzzy inference system inferred 32.5% performance degradation and that the value completely belongs to the 'Caution (C)' set, which is the final state of this system. Inference value of 0.5 represents 50% degradation, and it can be judged as an intermediate state that linguistically belongs to both 'Caution (C)' and 'Warning (W)'.

The knowledge required to configure the fuzzy rules can be collected from various sources such as literature, databases and expert advice. In this study, the two fuzzy sets of 'Caution' and 'Warning' were created for each input variable. There are several ways to generate fuzzy rules, and 'number of cases' was applied in this problem. As there are seven input variables and they are divided

Table 7
Results of fuzzy inference: complex degradation.

Degradation	Simulation		Fuzzy inference result		RMSE
	Degree	Linguistic value	Degree	Linguistic value	
HDL	33.0%	C	32.5%	C	5.79
	55.0%	W	65.0%	W	
	68.0%	W	67.5%	W	
LSP	29.0%	C	32.6%	C	7.53
	49.0%	C	50.0%	C or W	
	80.0%	W	67.5%	W	
TPI	25.0%	C	32.5%	C	4.77
	45.0%	C	44.0%	C	
	65.0%	W	61.7%	W	
PPPL	25.0%	C	32.5%	C	4.36
	51.0%	W	50.6%	W	
	63.0%	W	62.2%	W	
TL	30.0%	C	32.5%	C	9.10
	53.0%	W	46.2%	C	
	64.0%	W	50.0%	C or W	
HDL + LSP	30.0%	C	32.6%	C	4.69
	55.0%	W	56.7%	W	
	70.0%	W	77.5%	W	
HDL + TPI	25.0%	C	32.5%	C	4.84
	55.0%	W	57.8%	W	
	65.0%	W	67.5%	W	
HDL + PPPL	30.0%	C	50.0%	C or W	14.23
	55.0%	W	50.0%	C or W	
	80.0%	W	66.5%	W	
HDL + TL	25.0%	C	32.5%	C	13.72
	54.0%	W	52.5%	W	
	90.0%	W	67.5%	W	
LSP + TPI	35.0%	C	33.9%	C	1.66
	55.0%	W	54.1%	W	
	70.0%	W	67.5%	W	
LSP + PPPL	40.0%	C	32.5%	C	17.52
	60.0%	W	45.2%	C	
	80.0%	W	54.6%	W	
LSP + TL	25.0%	C	32.5%	C	6.02
	40.0%	C	46.8%	C	
	70.0%	W	67.5%	W	
TPI + PPPL	40.0%	C	32.5%	C	14.15
	60.0%	W	40.3%	C	
	80.0%	W	67.5%	W	
TPI + TL	30.0%	C	32.6%	C	7.94
	55.0%	W	45.4%	C	
	70.0%	W	60.5%	W	
PPPL + TL	20.0%	C	50.5%	W	24.78
	40.0%	C	67.5%	W	
	55.0%	W	67.5%	W	

into two fuzzy sets, 2^7 Fuzzy rules can be made. Table 5 below shows the principle of fuzzy rule generation.

4. Results

This section describes simulation procedures, analysis methods, and significant results to demonstrate the applicability and performance of the FIS consisting of the above two NPP models, 1000 MWe and 1400 MWe.

As explained in Section 3, random performance degradation phenomena were simulated and the results were normalized to verify whether the system can perform proper inference when the normalized result is entered into the fuzzy inference system.

Since the range of the simulation for the fuzzy inference system was set to 0.1% reduction in the output caused by the given phenomenon, simulation was carried out within this range. First, performance degradation of 'High Drain Level' was simulated to 33%, 56% and 70%, and the simulation results were inferred to show 40.7%, 65% and 67.5% failure, respectively, for each case. Although these values do not accurately agree because fuzzy sets were determined by two membership functions using simple triangular and trapezoidal shapes, they can be easily understood based on the composition of fuzzy sets in the conclusion part. As the range of the 'Caution (C)' set was [0, 0.65] and the range of the 'Warning (W)' set was [0.35, 1], the inference result can be obtained by observing the degree of membership of the fuzzy inference value to the sets. For instance, a value of 0.407 is an inference result extremely close to 'Caution', and 0.65 and 0.675 can be interpreted as 'Warning'. This confirms that the fuzzy inference system can make proper inference. Table 5 below summarizes the verification results on performance degradation phenomena. The degree of simulation is direct input value in PEPSE by researcher. The degree of simulation and the fuzzy inference value turn out to be similar. They do not accurately coincide because changes in the variables for each performance degradation are not linear. High fuzzy inference values compared to the degree of simulation can be interpreted as a quick approach of variables to their peaks.

This paper classified the severity of performance degradation into caution and warning categories, but if fuzzy set section in conclusion part is subdivided, more groups can be created. The objective of this study is to detect performance degradation of a feedwater heater and distinguish its severity. This study attempted to present relevant methods commonly used. As shown in Tables 6 and 7, a difference in the linguistic value of simulation ('C' or

'W') and linguistic value of fuzzy inference result ('C' or 'W') is some sort of error. The results including RMSE (Root Mean Squared Error) were added for all performance degradation cases so that results can be compared easily. Even though there are a bit fluctuations between two tables, the accuracy of the proposed model was generally comparable for each degradation mode, so it was concluded that the proposed model is able to be applicable to the major NPP fleets in Korea.

Another objective of this study is to validate the applicability of the fuzzy inference method for applications in other power plants instead of being limited to specific power plants. A 1000 MWe model was applied to form the fuzzy inference system with a 1400 MWe PWR model to confirm whether performance degradation can be diagnosed. The simulation procedure is identical to the procedure described in Section 3.

Performance degradation phenomena were simulated through a sensitivity analysis, and the results were normalized and entered into the fuzzy inference system. Table 6 shows the results of fuzzy inference. Out of 45 simulation times for PEPSE performance, 39 FIS results showed correct. Such inference was made possible because the thermodynamic role of the feedwater heater remains identical, regardless of the power plant model. When the same type of performance degradation occurs in devices that perform the same role, the trend of change in for each variable is also the same.

There is no need for creating a new system to apply to different power plants, and the proposed system can be applied to the same device used in every power plant model. In Table 7, out of 45 simulation times for PEPSE performance, 39 results showed correct. Mostly caused many errors in reasoning associated with TL. This is considered due to the normalized values of TL is small. If a normalization value is small, it should act sensitively to the result of the inference. In other words, when a normalized value is minor, the inference result is likely to be oriented to make conservative or serious outcome.

5. Conclusions

In this paper, inference of the type and severity of performance degradation using data from a feedwater heater in a power plant was studied. A fuzzy inference methodology that allows for qualitative and quantitative inferences was proposed, and various cases were simulated and tested using the fuzzy inference system. After simulating single modes of performance degradation, double degradation modes were added to configure a fuzzy inference system for 15 performance degradation phenomena.

A method that uses diagnosis table to infer performance degradation, accomplished by observing variations of the data, served as the foundation that organizes the fuzzy rule. Fuzzy theory was introduced into the above-mentioned method in order to classify the severity of the inferred performance degradation, which is significant in that a quantitative factor was introduced into a qualitative method. While a method that uses a regression model consisting of quantitative calculations via matrix calculations has its strengths, such a method is sensitive to noise and has poor stability. Fuzzy theory improves stability because it calculates the overall effect based on rules rather than depending on every variable. A diagnosis table of the performance degradation was created using simulation software through a sensitivity analysis. This diagnosis table is more detailed than existing diagnosis tables, and it can identify more performance degradation phenomena. The fuzzy inference used in this study considers seven variables, which requires the installation of eight temperature, pressure, and flow sensors in the feedwater heater. Simulation and the diagnosis table verified that the inferred performance degradation could differ according to the variables. Unlike existing methods that do not make use of variables with small changes for inference, this study utilized variables with small changes for inference. Consequently, an increased number of observed variables can increase the number of performance degradation phenomena inferred. Variables cannot be recklessly added and it may be impossible to distinguish between overlapping degradation phenomena, but there is a sub-optimal advantage in that phenomena that do not appear as the result of inference can at least be excluded from consideration.

As a result, the generality of the fuzzy inference system was validated. Since the thermodynamic function and role of the feedwater heater remains the same for all power plants, the trends of change in the variables for performance degradation were also confirmed to be the same through simulation. This means that the fuzzy inference system can be applied to all power plant models in the same way. Early build of fuzzy inference system should be made manually based on knowledge of experts so adaptive FIS methods were not used in this paper. Thereafter information which is not inferred from the current FIS can be classified and relearned when clustering technique is implemented later.

Consequently, more measurement inputs, accurate knowledge and elaborate composition of fuzzy sets can allow for a more accurate diagnosis of the performance degradation in power generation devices, which can contribute to the efficient management of power plants.

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