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Fuzzy rule-based inference of reasons for high effluent quality in municipal wastewater treatment plant

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Abstract−A fuzzy inference system (FIS), which could classify the state of effluent quality if it was high or not and identify visually the reasons for the high effluent quality in municipal wastewater treatment plants (WWTPs), was developed in this study. The decision tree algorithm and fuzzy technique were applied in the development of this system. By applying the classification and regression tree (CART) algorithm as a decision tree algorithm, the knowledge related to effluent quality was extracted and IF-THEN rules with crisp boundary values were generated. By applying the fuzzy technique, the fuzzification of these rules was conducted, where the trapezoidal and triangular membership function was used as a membership function type. And a Mamdani model with the Max-min operation was used as an inference model and the center of area (CoA) method was used for deffuzification. The accuracy achieved by using the developed system to classify the effluent state was confirmed by comparing the result with measured data. Furthermore, the developed system was demonstrated to be a useful tool for inferring the reasons for the high effluent quality.

Key words: Rule Generation, Decision Tree, Fuzzy Inference, Diagnosis, Wastewater Treatment Plant

INTRODUCTION

Instrumentation, control and automation technology has been applied worldwide to the stable and economic field operation of municipal wastewater treatment plants (WWTPs). However, the accident diagnosis and decision support in WWTPs, which can infer the reasons for accidents and provide solutions to solve them, are still conducted by human operators based on their knowledge and experience. This manual diagnosis and decision support for the stable operation and management of WWTP has some disadvantages [1-3]. The manual diagnosis and decision support could be performed based on the human operators' subjective judgments, which may not sometimes be generally accepted. Furthermore, the operators cannot suggest proper solutions for problems beyond their knowledge. If the WWTP is operated by human experts with extensive knowledge and experience, the diagnosis and decision support can be properly achieved. Unfortunately, not all operators are experts, as such expertise requires long-term experience in the domain of WWTP's operation and management [4].

To overcome the limitations of the diagnosis and decision support by a human operator, some researchers have suggested the development of a decision support system (e.g., knowledge-based system, expert systems) by using data mining technologies such as multivariate statistical analysis, fuzzy logic, and neural networks [4-12]. They showed the extraction of knowledge and the generation of rules from historical data sets could be achieved by applying data mining technologies and that a decision support system could be developed based on the extracted knowledge and the generated rules. And it was demonstrated that the developed decision support system could partly replace the human operator's role in the domain of diagnosis for the stable operation and management of WWTP. However, the proposed decision support systems had some limitations. Some of the studies were only performed using the well-controlled pilot plant rather than field plants, for example, the A2O pilot plant for Baeza et al. [5,6], the SBR pilot plant for Kim et al. [8], the pilot scale hybrid anaerobic digester (UASB-AF) for Polit et al. [10] and Carrasco et al. [11], and the two-stage lab scale anaerobic digester for Murnleitner et al. [12]. And some of their research only examined the conceptual introduction on the decision support system such as the structure of system or the system principal, without the validation of system with data [4,7].

As part of a decision support system that can be practically used in real field plants, a fuzzy inference system (FIS), which can classify the state of effluent chemical oxygen demand (COD), suspended solid (SS) and total nitrogen (TN), and identify visually the reasons for the high effluent state, was developed in this study. To achieve this, long-term operation data were obtained from a field plant and data mining technologies such as decision tree algorithm and fuzzy logic technique were applied. The next sections provide a theoretical explanation of the data mining technologies that are used in this study, a detailed explanation on how to extract the knowledge and how to generate the rules from the obtained long-term data for the development of the FIS by using these kinds of data mining technologies.

MATERIAL AND METHODS

To develop an FIS, this study was performed according to the procedure as shown in Fig. 1. First, data were collected from the field plant. A decision tree algorithm was used to extract the knowledge and generate the rules to identify the main variables affecting

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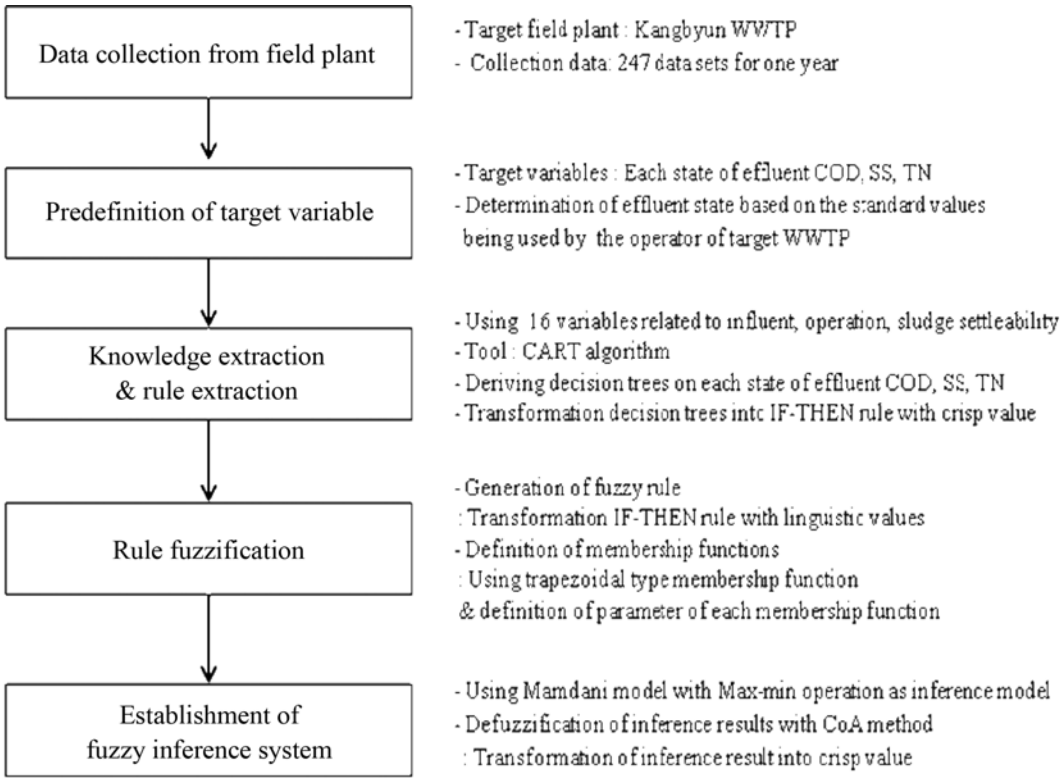

Fig. 1. Procedure for the system development.

the state of effluent quality and to examine how the distribution of these variables affects the state of effluent quality. Based on the results derived from the application of decision tree algorithm, rule fuzzification such as the generation of fuzzy rule and the definition of membership function was performed. Finally, FIS was established after the classification performance was estimated. For reference, FIS was implemented by using Matlab Fuzzy Logic Toolbox (Ver. 2006a) in this study. The methods are described in detail below.

1. Data Collection

The Kangbyun WWTP, located in Busan city, South Korea, and constructed in 2001, was chosen as the target WWTP for the FIS development. The plant, which treats municipal and industrial wastewater, has a design treatment capacity of 285,000 m^3/d. The WWTP was designed as a Bardenpho process consisting of a primary clarifier, pre-anoxic basin, pre-aerobic basin, post-anoxic basin, post-aerobic basin and secondary clarifier. Data related to influent entering the pre-anoxic basin, effluent, operating conditions and sludge settleabilty, etc. were collected for one year from the target filed plant.

2. Knowledge Extraction and Rule Generation from Historical Data Sets Using CART Algorithm

FIS is the one to perform the inference based on IF-THEN rules that are expressed by linguistic values. The most important element is the establishment of a rule-base in the FIS development. This requires the extraction of some specific knowledge related to effluent quality of the target WWTP, such as identifying the main variables affecting each effluent quality and how the distribution of these main variables affects the state of effluent quality. Next, the generation of rules in the form of IF-THEN based on the extracted knowledge is necessary to provide a basis for the establishment of a rule-base in the FIS.

Generally, the methods for knowledge extraction and rule generation can be classified into two categories: manual method and automatic method [3]. The general knowledge, which is theoretical and already existing for general WWTP management, can be extracted by manual methods such as literature survey and expert interview. The specific knowledge, which reflects the particular properties of the target WWTP that are immanent in the accumulated data, can be extracted by automatic methods such as machine learning technique. In this study, the automatic method for knowledge extraction and rule generation was applied due to its ease of knowledge acquisition and rule extraction, the reduction of variables that need to be considered for reaching a certain conclusion, and the discovery of new particular knowledge that is not obtained from the expert. In contrast, the manual method has some disadvantages such as the lack of experts with extensive experience and knowledge, and the difficulty in formulating the experts' knowledge for solving day-to-day problems.

A decision tree algorithm was applied as an automatic method to extract some knowledge and generate IF-THEN rules from the historical data sets obtained from the field plant in this study. A decision tree is an algorithm that learns from a given data set and then generates some rules for the classification, segment and prediction of target variables [8,13]. By applying a decision tree algorithm, some knowledge related to target variables is expressed in the form of tree, namely, a decision tree, and IF-THEN rules with crisp boundary values are generated based on the derived decision tree. Many decision tree algorithms have been reported in the literature: CART, C4.5, ASSISTANT, CHAID, QUEST, RIPPER, and so on. Among these, the classification and regression tree (CART) algorithm, which is commonly used in various fields and is the most widely used to classify nominal data [14], was chosen as the decision tree algorithm in this study. In the CART algorithm, a binary split is performed and a child node is generated in the direction that gives the greatest decrease in the Gini Index, as expressed in Eq. (1).

$$G = 1 - \sum_{j=1}^{c} (n_j/n)^2 \tag{1}$$

Where c is the number of groups classified, n is the number of data set, and n_j is the number of data set belonging to the j^{th} group (here, high or low group).

To apply a decision tree algorithm, the target variable to be classified should be predefined [13]. In this study, the target variable, that is, each state of effluent COD, SS and TN on each day, was predefined using the standard values that were being applied by the operator in the target WWTP to estimate if each effluent quality was high or not. This standard value is 19.9 mg/*l* for COD, 8.2 mg/*l* for SS and 16.7 mg/*l* for TN. The implementation of CART was performed with SPSS ANSWER TREE (VER.3.0), which is commercial software for multivariate statistical analysis.

3. Development of the Fuzzy Inference System (FIS) Using Fuzzy Logic Technique

FIS is generally implemented through the procedure of fuzzification of crisp input values, inference and defuzzification [15]. To develop an FIS, the rules were fuzzified based on IF-THEN rules with crisp boundary values that were derived from the application of the CART algorithm. Through the fuzzification, IF-THEN rules with crisp boundary values were transformed into rules with linguistic values (for example, small, middle and large), and the membership functions on each input and output variable were defined. Among the many types of membership function, trapezoidal and triangular membership functions were used in this study because of their simplicity and ease of use in optimizing the parameters of the membership functions. Each parameter of membership functions on input and output variables was determined by trial and error, where the crisp boundary values of the IF-THEN rules derived from the application of the CART algorithm were used as the basis to determine each parameter.

A Mamdani model with max-min operation was used as the fuzzy inference model, as this is the most commonly used fuzzy methodology [16]. The center of area (CoA) method was applied for the defuzzification to transform the fuzzy output derived with the max-min operation into a single crisp value. In this study, 12 data sets representing each state of effluent quality, that is, 6 data sets for high effluent quality and 6 data sets for low effluent quality, were used to develop the FIS and the rest of data sets (i.e., 235 data sets) were used to validate the performance of the developed FIS.

4. Theory on the Inference Procedure by the Fuzzy Inference System (FIS)

The procedure of fuzzy inference with the Mamdani model and CoA method can be explained as follows. Let's consider two fuzzy rules with two inputs and one output, as shown in Eq. (2). For reference, the part "x is A1 and y is B1" is called the antecedent, the part "z is C1" is called the consequent in fuzzy rule or fuzzy IF-THEN rule.

$$\begin{aligned}&\text{Rule 1: IF x is } A_1 \text{ and y is } B_1 \text{ THEN z is } C_1\\&\text{Rule 2: IF x is } A_2 \text{ and y is } B_2 \text{ THEN z is } C_2\end{aligned} \tag{2}$$

Where, A_1, B_1, A_2, B_2, C_1 and C_2 are fuzzy set, $A_1, A_2 \subset X$ (A_1, A_2 is subset of support set X), $B_1, B_2 \subset Y$ and $C_1, C_2 \subset Z$. If two inputs are crisp values x_0 and y_0, the membership degree of each rule on these inputs is calculated as shown in Eq. (3).

$$\begin{aligned}W_1 &= \mu_{A_1}(x_0) \wedge \mu_{B_1}(y_0) = \mathrm{MIN}(\mu_{A_1}(x_0), \mu_{B_1}(y_0))\\W_2 &= \mu_{A_2}(x_0) \wedge \mu_{B_2}(y_0) = \mathrm{MIN}(\mu_{A_2}(x_0), \mu_{B_2}(y_0))\end{aligned} \tag{3}$$

Where, W_1 and W_2 are the membership degree of rule 1 and rule 2, respectively, $\mu_{A_1}(x_0)$ and $\mu_{A_2}(x_0)$ are the membership degrees of A_1 and A_2 at x_0, $\mu_{B_1}(x_0)$ and $\mu_{B_2}(x_0)$ are the membership degree of

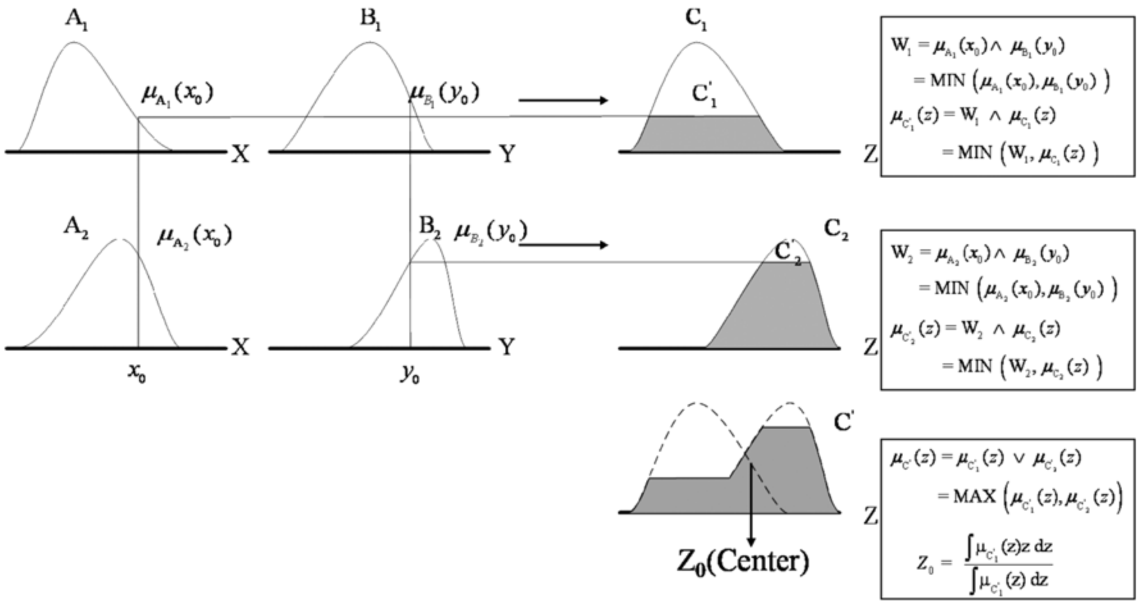

Fig. 2. Example of inference procedures with Mamdani model and CoA method.

B_1 and B_2 at y_0. Each inference result is derived as shown in Eq. (4) after mapping each membership degree of rule 1 and rule 2 on two inputs at the fuzzy set of consequent. The final inference result, namely, the final fuzzy output, is calculated as shown in Eq. (5).

$$\mu_{C_1'}(z)=W_1 \wedge \mu_{C_1}(z)=\text{MIN}(W_1, \mu_{C_1}(z))$$
$$\mu_{C_2'}(z)=W_2 \wedge \mu_{C_2}(z)=\text{MIN}(W_1, \mu_{C_1}(z)) \tag{4}$$

$$\mu_{C'}(z)=\mu_{C_1'}(z) \vee \mu_{C_2'}(z)=\text{MAX}(\mu_{C_1'}(z), \mu_{C_2'}(z)) \tag{5}$$

Finally, the final fuzzy output is transformed into a crisp output by applying the CoA method, as expressed by Eq. (6), which is called defuzzification.

$$Z_0=\frac{\int \mu_{C_1'}(z)z\,dz}{\int \mu_{C_1'}(z)dz} \tag{6}$$

This procedure of fuzzy inference with the Mamdani model and CoA method can be briefly expressed as shown in Fig. 2.

RESULTS AND DISCUSSION

1. Knowledge Extraction and Rule Generation with CART Algorithm

By applying the CART algorithm, each decision tree for effluent COD, SS and TN was generated, as shown in Fig. 3, when 247 data sets consisting of 16 variables shown in Table 1 were given as inputs. These decision trees could be represented as the following IF-THEN rules with crisp boundary values for human readability, and then used to establish the rule base in FIS.

IF-THEN rules for effluent COD:
Rule 1: IF X1≤13.85 and X5≤6587.5, THEN effluent COD<19.9
Rule 2: IF X1≤13.85 and X5>6587.5 and X14≤5467.5, THEN effluent COD>19.9
Rule 3: IF X1≤13.85 and X5>6587.5 and X14>5467.5, THEN effluent COD<19.9
Rule 4: IF X1>13.85 and X10≤4.34, THEN effluent COD<19.9
Rule 5: IF X1>13.85 and X10>4.34, THEN effluent COD>19.9

IF-THEN rules for effluent SS:
Rule 1: IF X1≤13.85 and X16≤100.58, THEN effluent SS>8.2
Rule 2: IF X1≤13.85 and X16>100.58 and X4≤97628, THEN effluent SS>8.2
Rule 3: IF X1≤13.85 and X16>100.58 and X4>97628, THEN effluent SS<8.2
Rule 4: IF X1>13.85 and X13≤0.725, THEN effluent SS<8.2
Rule 5: IF X1>13.85 and X13>0.725 and X10≤3.99, THEN effluent SS<8.2
Rule 6: IF X1>13.85 and X13>0.725 and X10>3.99, THEN effluent SS>8.2

IF-THEN rules for effluent TN:
Rule 1: IF X1≤15.35 and X5≤3842.5 and X2≤7.28, THEN effluent TN<16.7
Rule 2: IF X1≤15.35 and X5≤3842.5 and X2>7.28, THEN efflu-

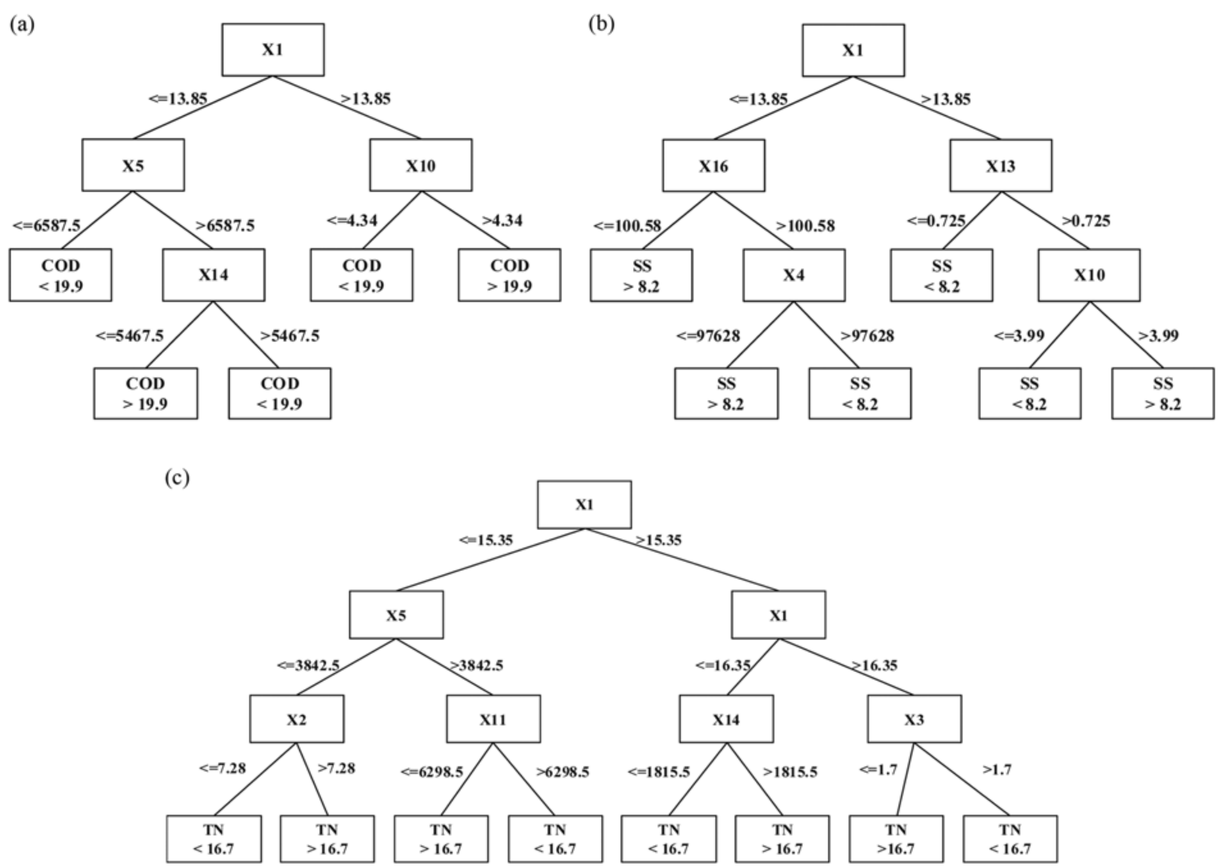

Fig. 3. Decision trees for effluent COD, SS and TN.

Table 1. Input variables used to develop each decision tree for effluent COD, SS and TN

Items	Variables	Description	Units
Influent	X1	Temperature	°C
	X2	pH	-
	X3	Ratio of influent carbon and nitrogen (C/N)	-
	X4	Flow rate	$m^3\ d^{-1}$
	X5	Biological oxygen demand (BOD) loading rate	$kg\ d^{-1}$
	X6	Chemical oxygen demand (BOD) loading rate	$kg\ d^{-1}$
	X7	Suspended solid (SS) loading rate	$kg\ d^{-1}$
	X8	Total nitrogen (TN) loading rate	$kg\ d^{-1}$
	X9	Total phosphate (TP) loading rate	$kg\ d^{-1}$
Operation conditions	X10	Dissolved oxygen (DO) concentration in aerobic basin	$kg\ d^{-1}$
	X11	Mixed liquor suspended solid (MLSS) concentration	-
	X12	Internal sludge return ratio	-
	X13	Sludge return ratio	$m^3\ d^{-1}$
	X14	Amount of wasted sludge	
Sludge settleability	X15	Sludge volume after 30 min settling (SV30)	$mL\ L^{-1}$
	X16	Sludge volume index (SVI)	$mL\ g^{-1}$

ent TN>16.7
Rule 3: IF X1≤15.35 and X5>3842.5 and X11≤6298.5, THEN effluent TN>16.7
Rule 4: IF X1≤15.35 and X5>3842.5 and X11>6298.5, THEN effluent TN<16.7
Rule 5: IF X1>15.35 and X1≤16.35 and X14≤1815.5, THEN effluent TN<16.7
Rule 6: IF X1>15.35 and X1≤16.35 and X14>1815.5, THEN effluent TN>16.7
Rule 7: IF X1>15.35 and X1>16.35 and X3≤1.7, THEN effluent TN>16.7
Rule 8: IF X1>15.35 and X1>16.35 and X3>1.7, THEN effluent TN<16.7

These results indicated that the state of effluent COD was affected by four variables-X1 (Temperature), X5 (BOD loading rate), X10 (DO concentration in biological reactor) and X14 (Amount of wasted sludge); the state of effluent SS by five variables-X1 (Temperature), X4 (Flow rate), X10 (DO concentration in biological reactor), X13 (Sludge return ratio) and X16 (SVI); and the state of effluent TN by six variables-X1 (Temperature), X2 (pH), X3 (Influent C/N ratio), X5 (BOD loading rate), X11 (MLSS concentration) and X14 (Amount of wasted sludge).

2. Development of Fuzzy Inference System (FIS)

IF-THEN rules with crisp boundary values that were derived by the CART algorithm were fuzzified to establish the rule-base in FIS. Through the fuzzification, the following fuzzy rules expressed by linguistic values were generated and the parameters of each membership function for input variables and output variables were identified, as shown in Table 2-4. Fig. 4 shows one example of the parameters indentified membership function: X1 for the inference of effluent COD.

Table 2. Parameters of trapezoidal membership functions for effluent COD

Variables	Range	Small	Large
X1	0-30	[0 0 12.8 19.9]	[12.8 19.9 30 30]
X5	0-6800	[0 0 5400 5800]	[5400 5800 6800 6800]
X10	0-5	[0 0 3.5 4.48]	[3.5 4.55 5 5]
X14	5000-23000	[0 0 5800 7040]	[5800 7040 23000 23000]
Effluent COD	0-28	[0 0 16 21]	[16 21 28 28]

Table 3. Parameters of trapezoidal membership functions for effluent SS

Variables	Range	Small	Large
X1	0-30	[0 0 10.7 15.7]	[10.7 14.7 30 30]
X4	73000-270000	[30000 73000 83020 100800]	[83020 118500 270000 270000]
X10	0-5	[0 0 3.85 4.24]	[3.85 4.24 5 5]
X13	0-1	[0 0 0.64 0.76]	[0.64 0.76 1 1]
X16	50-140	[50 50 87.76 105.9]	[97.76 105.9 140 140]
Effluent SS	0-20	[0 0 7.58 9.32]	[7.58 9.32 20 20]

Table 4. Parameters of trapezoidal and triangular membership functions for effluent TN

Variables	Range	Small	Middle	Large
X1	0-30	[0 0 11.5 16.1]	[15.3 15.9 16.5]	[16.1 19.5 30 30]
X2	5-8.5	[5 5 7.17 7.3]		[7.17 7.35 8.5 8.5]
X3	0-7	[0 0 1.6 2.1]		[1.6 2.1 7 7]
X8	0-8000	[0 0 3476 4305]	-	[3476 4029 8000 8000]
X11	1800-3800	[1800 1800 3200 3600]		[3250 3600 3800 3800]
X14	0-6800	[0 0 790.6 1820]		[1600 2400 6800 6800]
Effluent TN	5-22	[5 5 14.4 17.4]		[14.4 17.4 22 22]

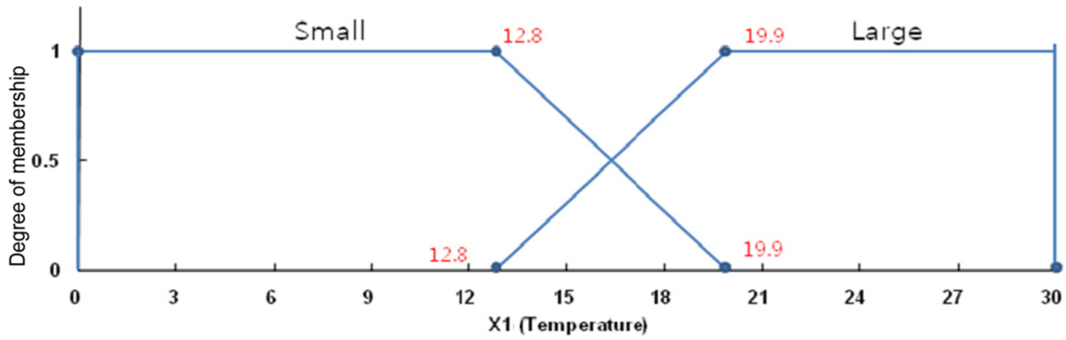

Fig. 4. Parameter identified membership function of X1 for inference of effluent COD.

Fuzzified rules for effluent COD:
Rule 1: IF X1 is small and X5 is small, THEN effluent COD is small
Rule 2: IF X1 is small and X5 is large and X14 is small, THEN effluent COD is large
Rule 3: IF X1 is small and X5 is large and X14 is large, THEN effluent COD is small
Rule 4: IF X1 is large and X10 is small, THEN effluent COD is small
Rule 5: IF X1 is large and X10 is large, THEN effluent COD is large

Fuzzified rules for effluent SS:
Rule 1: IF X1 is small and X16 is small, THEN effluent SS is large
Rule 2: IF X1 is small and X16 is large and X4 is small, THEN effluent SS is large
Rule 3: IF X1 is small and X16 is large and X4 is large, THEN effluent SS is small
Rule 4: IF X1 is large and X13 is small, THEN effluent SS is small
Rule 5: IF X1 is large and X13 is large and X10 is small, THEN effluent SS is small
Rule 6: IF X1 is large and X13 is large and X10 is large, THEN effluent SS is large

Fuzzified rules for effluent TN:
Rule 1: IF X1 is small and X5 is small and X2 is small, THEN effluent TN is small
Rule 2: IF X1 is small and X5 is small and X2 is large, THEN effluent TN is large
Rule 3: IF X1 is small and X5 is large and X11 is small, THEN effluent TN is large
Rule 4: IF X1 is small and X5 is large and X11 is large, THEN effluent TN is small
Rule 5: IF X1 is middle and X14 is small, THEN effluent TN is small
Rule 6: IF X1 is middle and X14 is large, THEN effluent TN is large
Rule 7: IF X1 is large and X3 is small, THEN effluent TN is large
Rule 8: IF X1 is large and X3 is large, THEN effluent TN is small

By applying the Mamdani model with Max-min operation as the

Table 5. Classification accuracy on each state of effluent COD, SS and TN

Items			COD		SS		TN	
			High	Low	High	Low	High	Low
Numbers	Measured	Developed	6	6	6	6	6	6
		Validated	45	190	51	196	56	179
		Total	51	196	45	202	62	185
	Misclassified	Developed	0	0	0	0	0	0
		Validated	6	0	4	1	2	1
		Total	6	0	4	1	2	1
Total Classification accuracy (%)			97.6		98.0		98.8	

inference model and the CoA method for the defuzzification of fuzzy output, each FIS for effluent COD, SS and TN was implemented. To confirm the proper development of each FIS, the classification on each state of effluent COD, SS and TN by FIS must be similar to the classification based on measured effluent data. Furthermore, when the effluent state is classified as high effluent state, the errors between the inferred high effluent quality and the measured high effluent quality should be small so that each FIS can be a useful tool for the inference of reasons for the high effluent quality. Table 5 shows the results of the classification on each state of effluent COD, SS and TN that were conducted by the developed FIS and measured data. The estimated average absolute difference between the inferred and the measured values for high effluent quality was 1.25 mg/L for effluent COD, 1.36 mg/L for effluent SS and 0.87 mg/L for effluent TN. As one of the examples showing the inference performance of the FIS developed in this study, the results of the inferred high effluent COD and the measured high effluent COD were compared in Fig. 5. These results revealed the high classification accuracy of each FIS with an effluent state-misclassification of less than 3% and small errors between the inferred and measured values. Therefore, it could be concluded that each FIS was properly developed. The next section explains how this inference system can be used for the inference of reasons for high effluent quality in detail.

3. Practical Use of FIS for the Inference of Reasons for the High Effluent Quality

The developed FIS can be used to infer the reasons for the high effluent quality by the visual identification of the main fuzzy rules that contribute to the high effluent quality or by quantitatively calculating how much a certain rule contributes to effluent quality. Fig. 6 shows one example that the FIS for effluent COD was implemented in Matlab Fuzzy Logic Toolbox at given input values. For the input variables shown in this figure (12.3 for X1, 13300 for X5, 3.3 for X10 and 620 for X14) effluent COD concentration was inferred as 23.0 mg/L, which belonged to the high effluent COD concentration. This case provided visual evidence that rule 2 contributes to the high effluent COD predominantly. Therefore, it could be said that the high effluent COD was attributed to low influent temperature (X1), high influent BOD loading rate (X5) and small amount of wasted sludge (X14). Additionally, it was possible to know that the increase of the wasting sludge at a secondary settler could be a possible solution to solve the problem of high effluent COD at given conditions.

CONCLUSION

By using data mining technologies such as the decision tree algo-

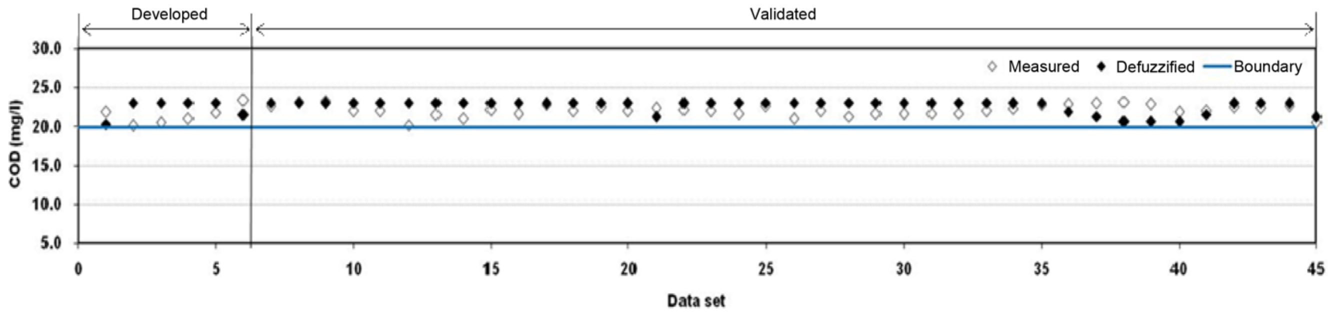

Fig. 5. Comparison between inferred effluent COD and measured effluent COD.

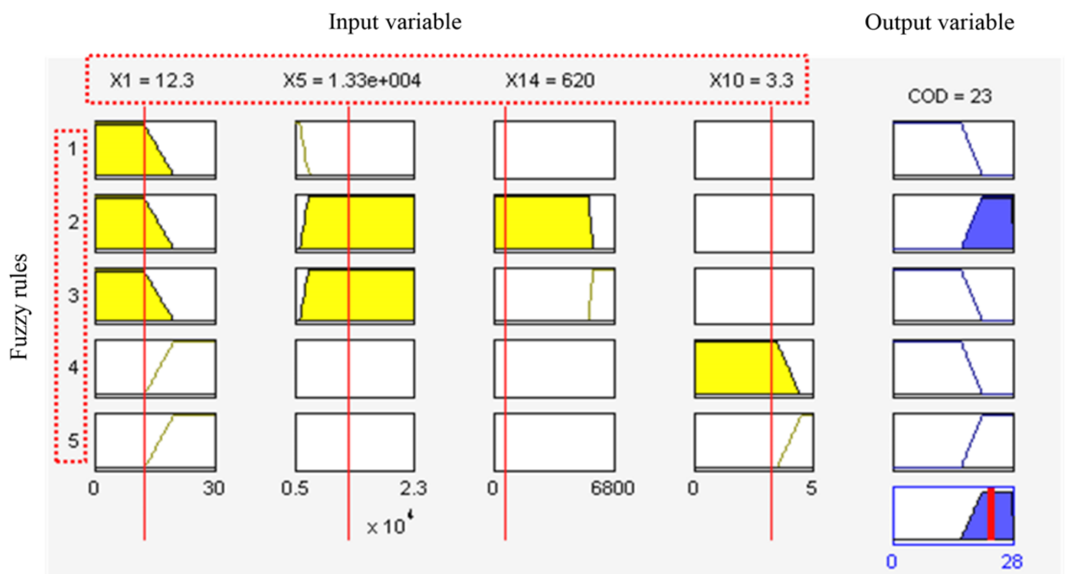

Fig. 6. Example of inferred result by fuzzy inference system for effluent COD.

rithm and fuzzy logic technique, an FIS that could properly classify the effluent state and identify visually the reasons for high effluent quality was successfully developed in this study. The application of this kind of FIS to the target WWTP will reduce the time required to identify the reasons for the high effluent quality due to the system's ease of use. Furthermore, a more objective inference will be obtained than that attained by a human operator because the system was developed based on the knowledge that is immanent in the data sets obtained from target WWTP. Consequently, the developed FIS will contribute to the stable operation of the target WWTP. Although the developed FIS can be a useful tool for diagnosis and decision support in WWTP operation, this system must be combined with the general knowledge acquisition system, which can be developed by reflecting the knowledge and experiences of human expert, in order to be a more powerful tool in the domain of diagnosis and decision support for the stable operation and management of WWTPs.

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