*Desalination and Water Treatment*
www.deswater.com
doi: 10.1080/19443994.2013.780757

51 (2013) 6184–6193
September

Taylor & Francis
Taylor & Francis Group

# A fuzzy neural network-based soft sensor for modeling nutrient removal mechanism in a full-scale wastewater treatment system

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Received 23 October 2012; Accepted 26 February 2013

ABSTRACT

The nonlinearity and complicated biological phenomena existing in wastewater treatment processes (WWTP) make the operation and modeling of WWTP quite difficult. In this study, a hybrid learning method combining genetic algorithm with adaptive neuro-fuzzy inference system (GA-ANFIS) was serviced to estimate effluent nutrient concentrations in a full-scale biological wastewater treatment plant. The GA-ANFIS possessing a more flexible hybrid learning ability was adopted to capture the nonlinear relationships between the influent and effluent concentrations of pollutants. Having the capabilities of global and parallel optimization, GA was used to optimize the structure parameters of the fuzzy membership functions of GA-ANFIS. The real data collected from Korean Daewoo nutrient removal wastewater treatment plant were used to demonstrate the prediction efficiency of the proposed soft sensor with the aid of three performance indices of root mean square error, mean absolute percentage error, and squared correlation coefficient. The results indicate that the hybrid GA-ANFIS soft sensors outperform ANFIS-based soft sensors in terms of effluent prediction accuracy.

*Keywords:* Adaptive neuro-fuzzy inference system; Genetic algorithm; Modeling; Nutrient removal mechanism; Wastewater treatment

## 1. Introduction

Aiming at providing reliable online product quality or other hard-to-measure variables of unmeasured variables, soft sensors have gained increasing research interest in many process industries [1,2]. Soft sensors have been applied to many applications primarily including on-line prediction, process monitoring, process fault detection, and sensor validation containing sensor fault detection, identification, and reconstruction [1]. For the application of on-line prediction, several well-established and powerful linear statistical models such as partial least squares (PLS) [3] and principle component analysis or regression [4] have been extensively used for designing soft sensors. The original PLS algorithm can only accurately model linear relations between the process variables. Therefore, some advanced modifications or extensions of the PLS algorithm have been proposed. These modified versions

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*Presented at The Fifth Desalination Workshop (IDW 2012), October 28–31, 2012, Jeju, Korea*

include the multi-way PLS, the moving window PLS (MWPLS) and recursive PLS (RPLS) [1]. Both original PLS and RPLS regression models were used as indoor air quality soft sensors for the prediction of particulate matter concentrations in Seoul subway systems [5]. A fast MWPLS algorithm was developed and applied in a simulated continuous stirred tank reactor and an industrial air separation process [6]. A RPLS soft sensor was proposed to predict the biological oxygen demand (BOD) of a real wastewater treatment process (WWTP) [7]. Different from the traditional soft sensors that model the process at a global level, a local modeling method combining just-in-time learning technique with PLS was used in two industrial case studies of the Tennessee Eastman process (TEP) and a debutanizer column process [8]. In addition, a fuzzy PLS model was used to predict and monitor the treatment performance of a pilot-scale membrane bioreactor (MBR) [9].

However, when dealing with highly nonlinear processes, such as WWTPs, the prediction accuracy of these linear models may be decreased significantly. In order to capture the nonlinear characteristics of the process variables, some nonlinear soft sensors have been recently proposed. Typically, according to the soft sensors classification by Kadlec et al. [1], these nonlinear soft sensing techniques mainly consist of three classes: artificial neural network (ANN) [10], support vector machine (SVM) [11], and neuro-fuzzy system (NFS) [12]. ANN-based soft sensors can be found in many applications. For example, using ANN, Wu et al. [13] adopted ANN to predict the performance characteristics of a reversibly used cooling tower for a heat pump heating system. The authors first used a measuring index of mean squared error to determine the optimal number of neurons at the hidden layer in the ANN. Then, 11 back-propagation (BP) algorithms were compared and one BP algorithm that could get the best prediction results was used for the construction of ANN structure. Ráduly et al. [14] developed a reliable and rapid performance evaluation method for the prediction of effluent concentrations of ammonium, BOD, chemical oxygen demand (COD), total suspended solids (TSS), and total nitrogen (TN) in a simulated benchmark WWTP model. Similarly, Mjalli et al. [15] developed an ANN program as a valuable performance assessment tool to predict the effluent concentrations of BOD, COD, and TSS in a local wastewater treatment plant. Molga et al. [16] elaborated a hybrid first-principles neural network, which combines first-principles knowledge represented by a set of process differential equations with a neural network used as a nonparametric approximator, to obtain accurate prediction of the dynamic behavior of a biological textile wastewater treatment plant.

Due to the theoretical advantages in the statistical learning theory, SVM has been of increasing popularity not only in the computational learning community but also in many applications used as soft sensors. Yan et al. [17] proposed to use a fast SVM named least squares support vector machine (LSSVM) as a soft sensor to predict the freezing point of the light diesel oil in a fluid catalytic cracking unit. In their work, the Bayesian evidence framework was used for the optimal selection of the model parameters of LSSVM. In addition, SVM has recently applied to the process monitoring. Ge and Song [18] proposed to use a least squares support vector regression model as local modeling method for the monitoring of nonlinear multiple mode processes. Their method could provide better performance than conventional methods when tested with two case studies of a numerical example and the benchmark model of TEP. However, the main bottleneck of SVM lies in its computational complexity when dealing with very large data sets in the training process.

Another successful type of soft sensors is the NFS that is actually a hybrid modeling method. NFS combines the advantage of ANN with those of fuzzy inference system (FIS). Especially, the adaptive neuro-fuzzy inference system (ANFIS), which could achieve highly accurate prediction performance, has been recently a widely applied type of NFS. Pai et al. [19] developed three types of ANFIS, which varies with different combinations of influent variables based on the correlation coefficients between these influent variables and the effluent variables, to predict the effluent suspended solids and COD in a hospital wastewater treatment plant in Taiwan. Civelekoglu et al. [20] carried out a similar research using ANFIS to model the COD removal in a biological wastewater treatment plant. In the work of Huang et al. [21], an ANFIS-based soft sensor was employed to model the nonlinear relationships between the pollutants removal rate and the chemical dosages in a paper mill. This soft sensor was then used as an emulator representing the reaction process to provide the future predictions for a fuzzy neural network controller.

Although ANFIS has proven to be an effective tool to approximate any nonlinear functions, it has the main disadvantages of requiring long learning time and having slow convergence speed. Therefore, genetic algorithm (GA), which can be used for optimizing fuzzy rules and adjusting membership functions (MF) of fuzzy sets within the framework of ANFIS, could be combined with ANFIS to achieve a better prediction performance [22]. A structure or parameter learning algorithm based on GA was proposed to dynamically determine the fuzzy partitions of input and output spaces as well as the number of fuzzy sets and the MF of each fuzzy set [23]. The modeling, optimization, and control of WWTPs are challenging due to the nonlinear characteristics, complex interactions, and time variable hydraulic conditions in biologically activated sludge processes. In order to realize stable monitoring and control in the WWTP, it is very important to develop precise and timely soft sensors. Consequently, in this study, the hybrid algorithm called GA-ANFIS was applied to build a soft sensor for modeling the nutrient removal in a full-scale WWTP.

## 2. Materials and methods

### 2.1. Wastewater treatment process

The targeted system is the Daewoo nutrient removal (DNR) plant located in D city of Korea. As shown in Fig. 1, the plant mainly consists of four biological reactors, two clarifiers before and after the four reactors, a thickener tank and a dewatering system. The reactions of denitrification, anaerobic, anoxic and oxic processes take place in the four biological reactors from left to right. The measured process variables for soft sensor modeling have two categories: influent and effluent variables. The influent variables include flow rate, TSS, BOD, COD, TN and total phosphorous (TP), and the effluent variables include effluent COD, effluent TN, and effluent TP. The variations of these process variables for one year are shown in Fig. 2. The influent TN and TP exhibit regular fluctuations during one year, whereas the influent TSS, BOD, COD, and effluent COD show relatively lower concentrations in the summer and higher concentrations in the winter (Fig. 2(a) and (c)). The influent flow rate (Fig. 2(b)) has several abnormal values that may be the results of flow rate sensor failures. The real data used for modeling contained 357 samples measured between 10 March 2007 and 29 February 2008. The first 236 samples were used as training data and the rest were used as test data. The statistical values including mean and standard deviation values of the modeling data are listed in Table 1.

### 2.2. GA-ANFIS

ANFIS is a multilayer feed-forward network that uses neural network learning algorithms and fuzzy reasoning to map inputs into an output. It is a FIS implemented in the framework of adaptive neural networks [12]. Fig. 3 shows the architecture of a typical ANFIS with two inputs, two rules, and one output using Takagi–Sugeno–Kang (TSK) model [24,25], where each input is assumed to have two MFs.

The function of each ANFIS layer in Fig. 3 is summarized and explained as follows. For layer 1, all nodes are adaptive nodes that can generate membership values for inputs. The outputs of this layer are given by:

$$\begin{aligned} O^1_{A_i} &= \mu_{A_i}(x), \quad i = 1,2 \\ O^1_{B_j} &= \mu_{B_j}(y), \quad j = 1,2 \end{aligned} \tag{1}$$

where $x$ and $y$ are crisp inputs, and $A_i$ and $B_j$ are fuzzy sets characterized by the MFs with low, medium and high values.

For layer 2, the nodes are fixed, which are used as a simple multiplier. The outputs of this layer are represented by:

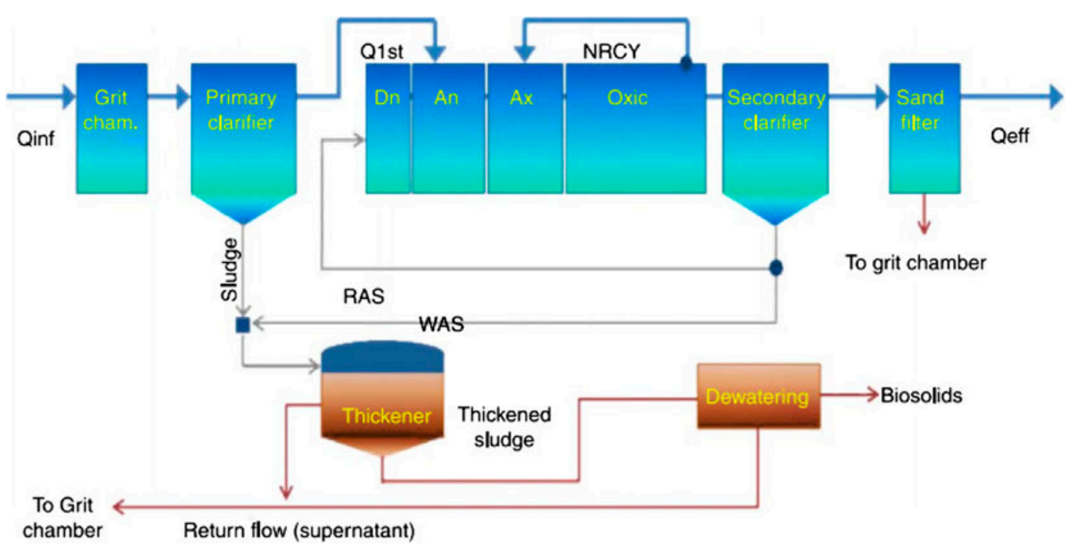


Fig. 1. The layout of DNR plant.

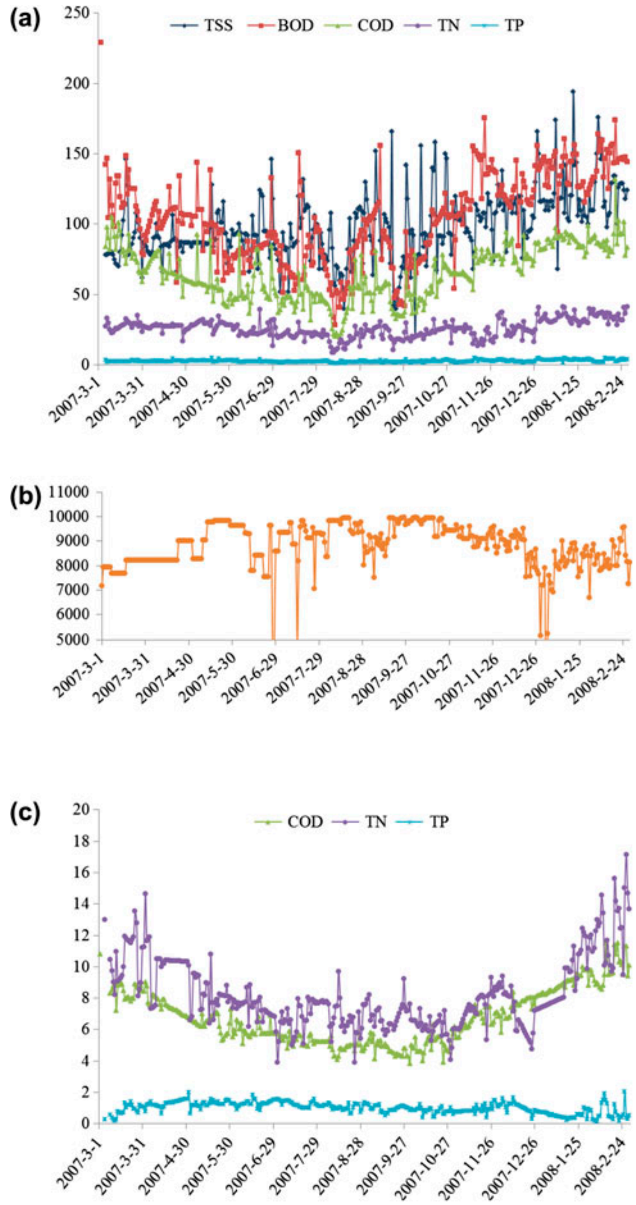


Fig. 2. Time series plots of (a) influent concentrations, (b) influent flow rate, and (c) effluent concentrations.

$$O_{ij}^2 = w_{ij} = \mu_{Ai}(x)\mu_{Bj}(y), \quad i,j = 1,2 \tag{2}$$

which represent the firing strength of each rule. The firing strength means the degree to which the antecedent part of the rule is satisfied.

For layer 3, the nodes are also fixed, indicating that they play a normalization role in the network. The outputs of this layer, which are called normalized firing strengths, can be represented as follows:

$$O_{ij}^3 = \bar{w}_{ij} = \frac{w_{ij}}{w_{11} + w_{12} + w_{21} + w_{22}}, \quad i,j = 1,2 \tag{3}$$

Table 1
The mean and standard deviation values of influent and effluent variables collected from the DNR plant

| Variable | Mean | Standard deviation | Unit |
|---|---|---|---|
| *Influent variable* | | | |
| Flow rate | 8845.6 | 892.1 | $m^3/d$ |
| TSS | 98.86 | 24.07 | g $SS/m^3$ |
| BOD | 103.93 | 30.42 | g $O_2/m^3$ |
| COD | 64.73 | 18.84 | g $COD/m^3$ |
| TN | 25.68 | 6.29 | g $N/m^3$ |
| TP | 2.68 | 0.75 | g $P/m^3$ |
| *Effluent variable* | | | |
| COD | 6.73 | 1.71 | g $COD/m^3$ |
| TN | 8.18 | 2.18 | g $N/m^3$ |
| TP | 1.01 | 0.36 | g $P/m^3$ |

For layer 4, the parameters in this layer are referred to as consequent parameters. Each node is an adaptive node, and its output is simply the product of the normalized firing strength and a first-order polynomial. The outputs of this layer are given by:

$$O_{ij}^4 = \bar{w}_{ij} f_{ij} = \bar{w}_{ij}(p_{ij}x + q_{ij}y + r_{ij}), \quad i,j = 1,2 \tag{4}$$

where $p_{ij}$, $q_{ij}$, and $r_{ij}$ are consequent parameters of the first-order polynomial.

For layer 5, the single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals.

$$O_j^5 = \sum_i \bar{w}_i f_i, \quad i = 1,2 \tag{5}$$

By combining the gradient descent optimization method and the least squares method, the hybrid learning algorithm could effectively improve the prediction performance of ANFIS. Thus, this algorithm was used to tune the adjustable parameters in this study.

Like the structure of ANFIS, GA-ANFIS is also a fuzzy inference system (FIS) implemented in the framework of adaptive neural networks (Fig. 4). It has five layers including an input fuzzy layer, a product layer, a normalized layer, a defuzzy layer, and an output layer. GA, inspired by the mechanics of natural selection, is superior to the traditional calculus-based optimization algorithms that usually find a local optimum solution. As a population-based optimization method, GA can simultaneously seek different regions in a solution space, which increases the likelihood of

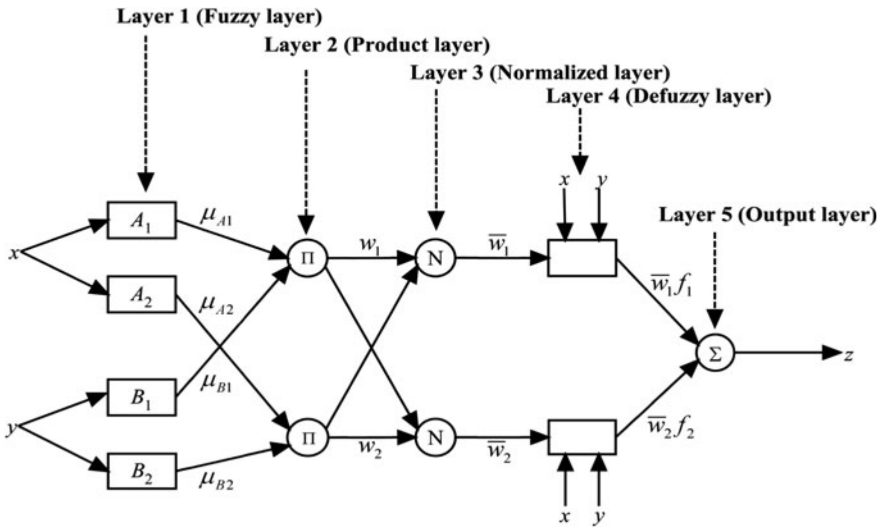


Fig. 3. ANFIS structure for a two-input TSK model with four rules.

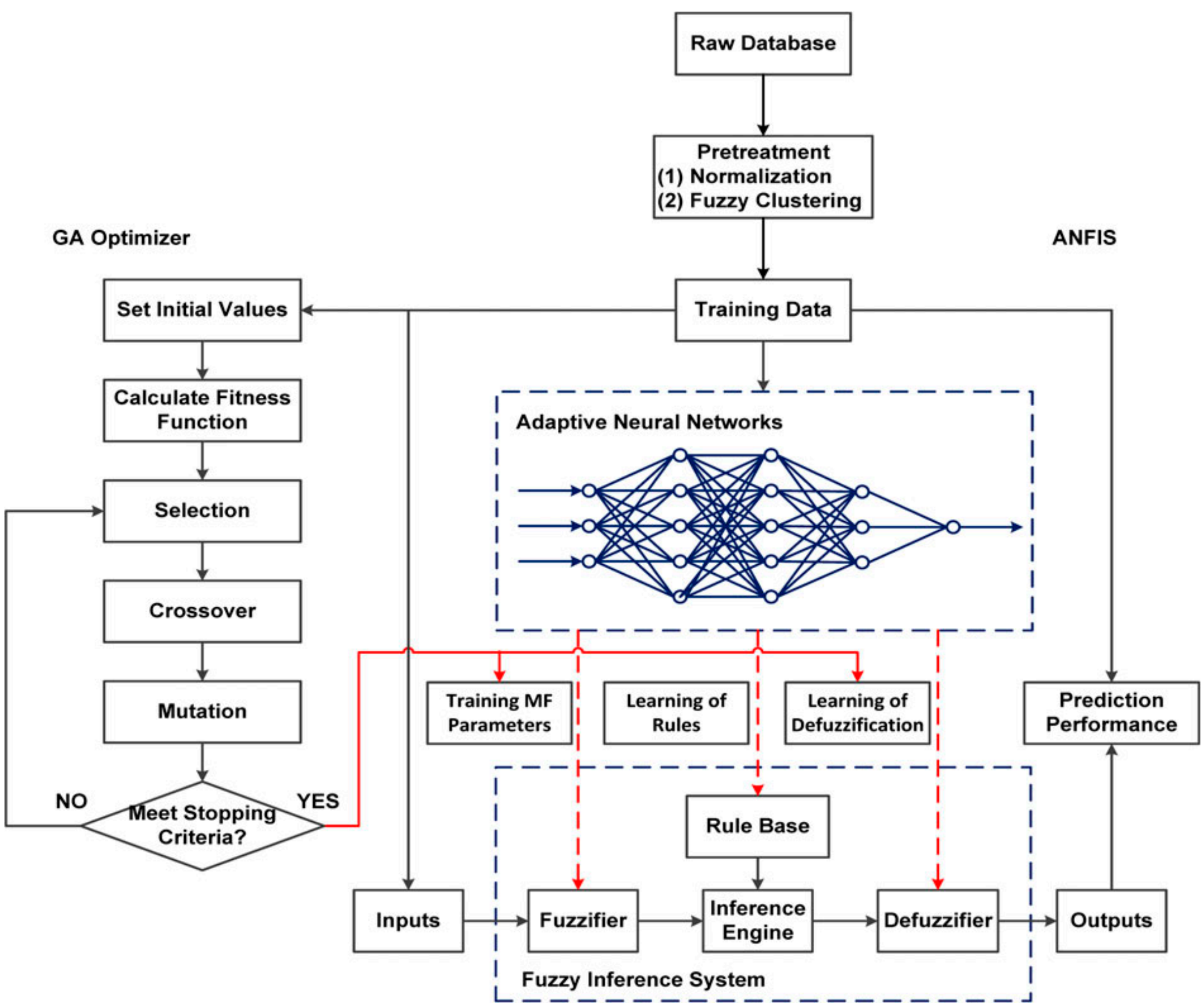


Fig. 4. The flow chart of GA-ANFIS.

finding a diverse set of global minima. During the learning stage, GA is used to optimize fuzzy rules and adjust MFs of fuzzy sets. In order to improve the system precision and reduce the calculation time, we use BP algorithm to train GA-ANFIS updating parameters of MFs and the linked weights between layers 4 and 5 on the basis of the first training stage.

In order to assess the prediction capability of ANFIS models, several performance indices including root mean square error (RMSE), mean absolute percentage error (MAPE), and squared correlation coefficient ($R^2$) are defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_i - p_i)^2} \tag{6}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|100 \times \frac{a_i - p_i}{a_i}\right| \tag{7}$$

$$R^2 = \frac{\mathrm{cov}(a,p) \times \mathrm{cov}(a,p)}{\mathrm{cov}(a,a) \times \mathrm{cov}(p,p)} \tag{8}$$

where $a_i$ is the experimental value, $p_i$ is the predicted value, $N$ is the number of data, and cov($a$, $p$) is the covariance between $a$ and $p$ sets.

## 3. Results and discussion

Since there are three output variables (effluent COD, effluent TN, and effluent TP) needed to predict in the DNR plant, three GA-ANFIS models were built for each output variable. To take the hydraulic characteristics in the WWTP into account, the effluent data of one day ago were included as additional input variables. Finally, nine input variables of six influent variables together with three historical effluent variables and three output variables were used for GA-ANFIS modeling and prediction. The modeling steps for these GA-ANFIS models are similar. In order to reduce unnecessarily wordy analysis, we just take the effluent COD as an example to show the main results.

For the effluent COD model, Matlab's fuzzy subtractive clustering function was employed and six clusters were determined. The ANFIS model of the effluent COD (Fig. 5) has five layers with nine nodes in the input layer and one node in the output layer. The second layer containing 54 (nine × six) nodes is used to calculate the MFs; the third layer with six nodes is the rule layer; and the fourth layer with six nodes is the normalization calculating layer. After training, the ANFIS model, the inference was performed according to six fuzzy linguistic rules for modeling effluent COD. After determining the initial value of the premise parameter and the architecture of

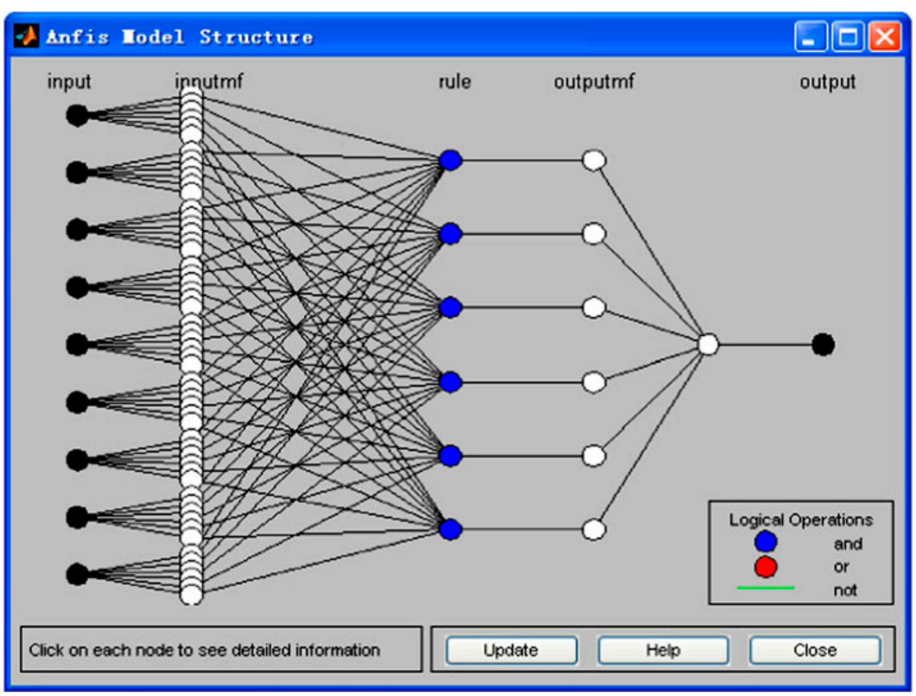


Fig. 5. The model structure of ANFIS for modeling the effluent COD.

the predictive model, the network was trained by hybrid algorithm. Then, the premise and consequent parameters of the network were pruned. MFs of the variables were drawn after the premise parameter was obtained.

GA was used as an optimizer for determining the optimal values of MFs parameters in the input and output layers. Fig. 6 exhibits GA-ANFIS training process. After 20 generations, both the sum squared error and fitness values converged at their steady points (Fig. 6(a)), which means the GA found optimal solutions for the parameters of ANFIS MFs, and of output consequence part. Using these optimized parameters, RMSE and step size values of ANFIS kept constant after approximately 200 epochs (Fig. 6(b)).

In the study, Gaussian type MF, which is one of the most widely used fuzzy MFs for the modeling of high-dimensional systems, was utilized to train the network. The Gaussian MF is determined completely by two parameters ($c$ and $\sigma$) as follows:

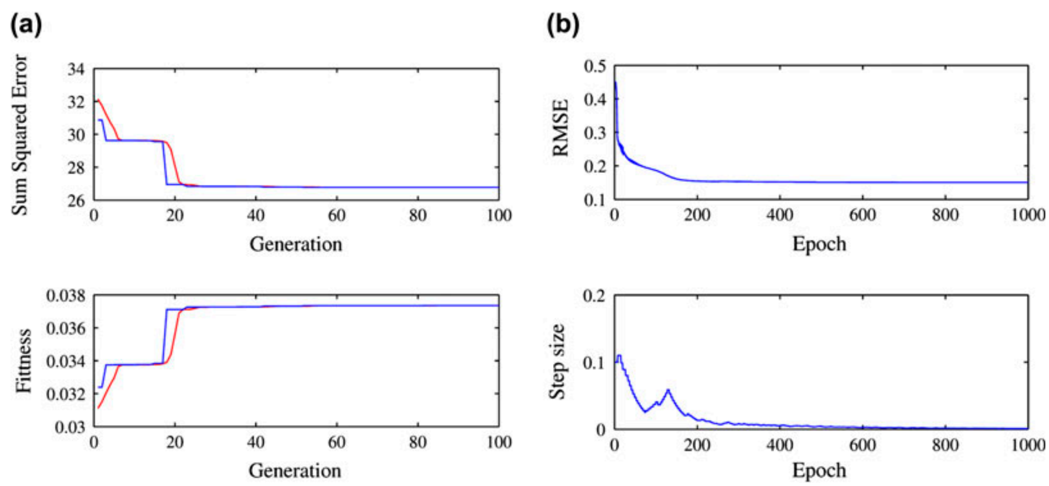


Fig. 6. Training process of the GA-ANFIS in terms of (a) GA step and (b) ANFIS step.

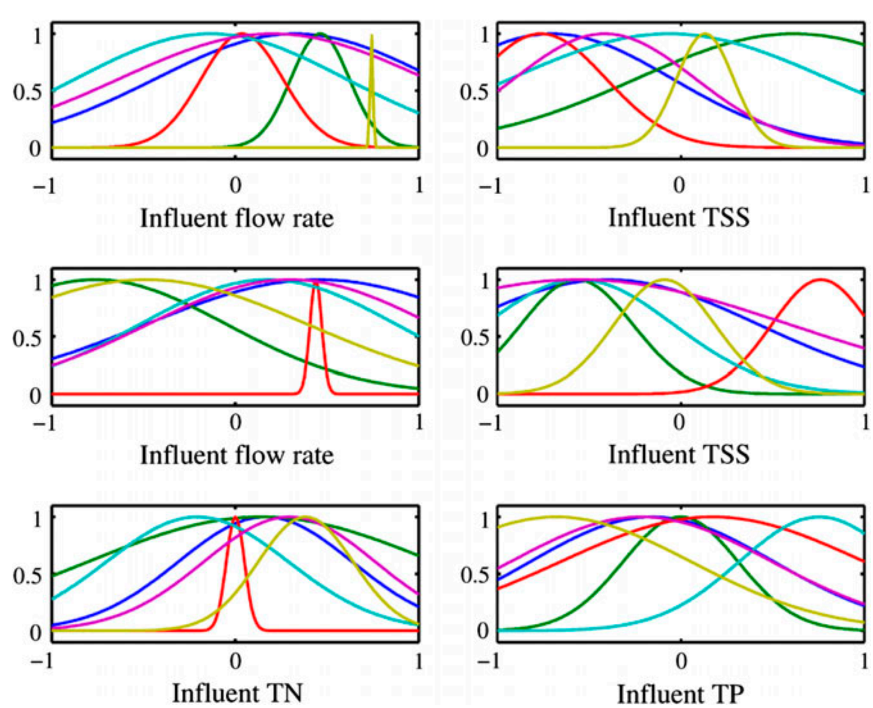


Fig. 7. The final input MFs after GA-ANFIS training.

$$\mu_{\text{Gaussian}}(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{9}$$

where $c$ and $\sigma$ represent the center and width of the Gaussian MF, respectively. The shapes of the first six input MFs after training process are shown in Fig. 7, where each graph contains six lines representing six clusters determined by Matlab's fuzzy subtractive clustering function. The number of clusters is a key parameter that can influence the computing speed and modeling accuracy of ANFIS model.

GA-ANFIS is a data-driven modeling method. A training model is trained first and then can be used to simulate the dynamics of DNR process. In more detail, the training parameters are optimized via a sum-squared error between the model predictions and the real outputs. With respect to the current application, the predictive model can be written as follows:

$$y(t+1) = f(u(t+1), y(t)) \tag{10}$$

where $y(t+1)$ and $u(t+1)$ represent the effluent and influent variables at time $t+1$, respectively, $y(t)$ means one yesterday effluent variable.

After training the network of GA-ANFIS, the system parameters such as the parameters of MFs, the number of clusters determined by subtractive fuzzy clustering partition, firing strengths and consequent parameters of the first-order polynomial can be used for prediction. The three-dimensional graphic surfaces of the defuzzified results of effluent COD to various influent water qualities are illustrated in Fig. 8. A nonlinear relationship of effluent COD to influent flow rate and influent TSS can be observed clearly from Fig. 8(a). On the other hand, there is almost a linear relationship between effluent COD and influent TN

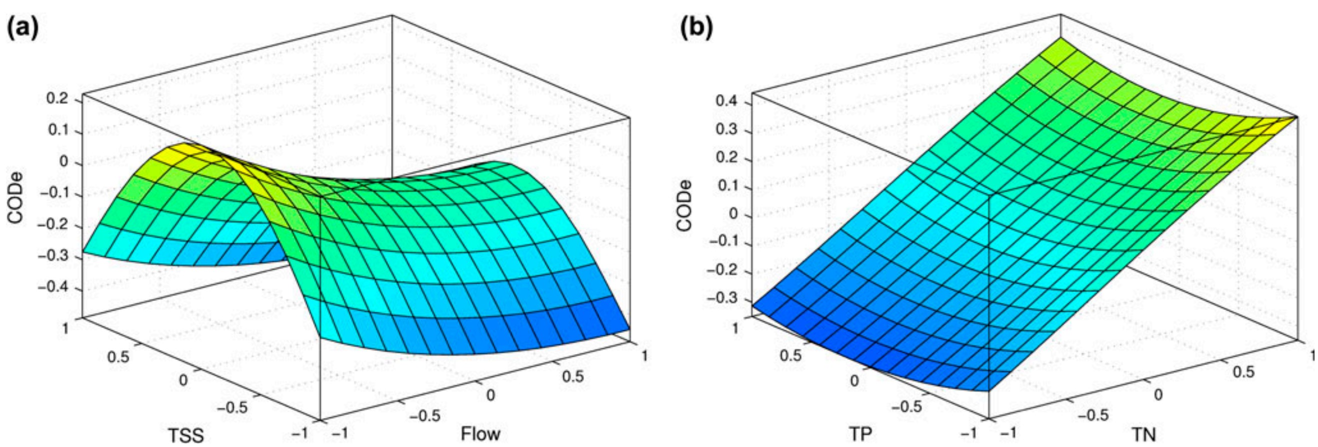


Fig. 8. Three-dimensional representations of the effluent COD response surface graph in terms of: (a) influent flow rate and influent TSS and (b) influent TN and influent TP.

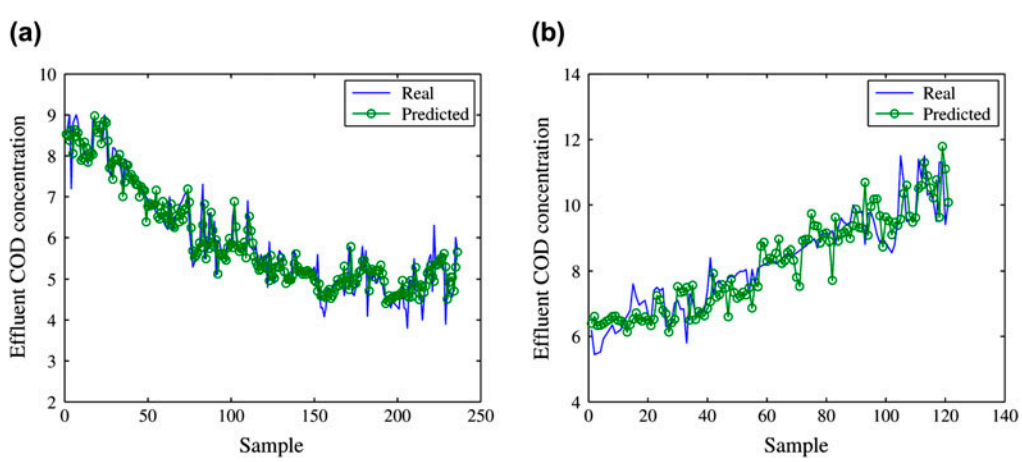


Fig. 9. Prediction accuracy of the GA-ANFIS using (a) training data and (b) test data.

Table 2
Comparison of performances of ANFIS and GA-ANFIS in modeling effluent COD, TN and TP concentrations

| Model | Training data | | | Test data | | |
|---|---|---|---|---|---|---|
| | RMSE | MAPE (%) | $R^2$ | RMSE | MAPE (%) | $R^2$ |
| *COD eff* | | | | | | |
| ANFIS | 0.290 | 3.705 | 0.950 | 0.782 | 7.100 | 0.748 |
| GA-ANFIS | 0.391 | 4.912 | 0.907 | 0.660 | 6.289 | 0.800 |
| *TN eff* | | | | | | |
| ANFIS | 0.686 | 6.548 | 0.860 | 2.035 | 19.263 | 0.523 |
| GA-ANFIS | 0.828 | 7.683 | 0.796 | 1.734 | 14.623 | 0.577 |
| *TP eff* | | | | | | |
| ANFIS | 0.182 | 14.711 | 0.597 | 0.360 | 60.890 | 0.251 |
| GA-ANFIS | 0.183 | 14.784 | 0.595 | 0.351 | 58.382 | 0.284 |

derived from the GA-ANFIS model. Interestingly, influent TP has little effect on the prediction of effluent COD (Fig. 8(b)). In other words, in order to reduce the computation time and simplify the structure of GA-ANFIS model the influent TP variable could be removed from the modeling variables without losing model precision.

The comparisons between real data and predicted values by GA-ANFIS are shown in Fig. 9. The prediction results of the effluent COD concentrations were both satisfactory for the training (Fig. 9(a)) and test data (Fig. 9(b)), indicating that a stable and accurate soft sensor for estimating the effluent COD concentrations could be obtained from GA-ANFIS model. The superior prediction performance of GA-ANFIS is due to its capability to capture any nonlinear relationship to any degree of accuracy between response variable and predictor variables by adjusting its weights through the iterative learning process. In addition, GA-ANFIS has the advantage of tolerating certain measurement noise and sensor faults [22]. This robust feature makes it still suitable for the case that the process variables have outliers or abnormal values like the influent flow rate in this work (Fig. 2(b)).

In order to numerically evaluate the prediction ability of the GA-ANFIS, three performance indices consisting of RMSE, MAPE, and $R^2$ are listed in Table 2. From Table 2, it can be seen that the GA-ANFIS had smaller RMSE and MAPE as well as bigger $R^2$ for the testing data sets than the ANFIS model. The results verify that the prediction accuracy of GA-ANFIS was superior to that of the normally used ANFIS. It should be noted that our results based on GA-ANFIS were better than the previous study where ANN was used to build prediction models for the same WWTP data [26]. However, the prediction accuracy for the effluent TP is lower than those for the effluent COD and TN (Table 2). The reason for the low accuracy of the GA-ANFIS for modeling the effluent TP may be that the effluent TP shows relatively regular variations not depending on different seasons (i.e., summer and winter, Fig. 2(c)). Therefore, its GA-ANFIS prediction model calculated based on the other influent and effluent variables that have seasonal variations may have large prediction errors. In order to improve the prediction accuracy for the effluent TP, additional measurement variables such as effluent TSS, effluent BOD and chemical dosage for TP control should be taken into account.

## 4. Conclusions

A hybrid learning algorithm of GA-ANFIS was used to model the nonlinear relationships between the influent pollutant variables and the effluent variables in a biological wastewater treatment plant. The combined method of GA and ANFIS is especially useful for highly nonlinear processes like WWTP. The results of hybrid GA-ANFIS in the full-scale plant showed satisfactory prediction performance. Compared with ANFIS, the proposed GA-ANFIS had superior performance and good generalization capability. Specifically, the RMSE, MAPE and $R^2$ values using GA-ANFIS were greatly improved for predicting effluent COD, effluent TN and effluent TP. The overall results indicate that the soft sensors based on GA-ANFS can be effectively applied to model nutrient removal mechanism in the wastewater treatment system.

**Nomenclature**

| | | |
|---|---|---|
| ANFIS | — | adaptive neuro-fuzzy inference system |
| ANN | — | artificial neural network |
| BOD | — | biological oxygen demand |
| COD | — | chemical oxygen demand |
| DNR | — | Daewoo nutrient removal |
| FIS | — | fuzzy inference system |
| GA | — | genetic algorithm |
| MAPE | — | mean absolute percentage error |
| MWPLS | — | moving window PLS |
| NFS | — | neuro-fuzzy system |
| PLS | — | partial least squares |
| RMSE | — | root mean square error |
| RPLS | — | recursive PLS |
| $R^2$ | — | squared correlation coefficient |
| SVM | — | support vector machine |
| TN | — | total nitrogen |
| TP | — | total phosphorous |
| TSK | — | Takagi–Sugeno–Kang |
| TSS | — | total suspended solid |
| WWTP | — | wastewater treatment plants |

## Acknowledgments

This study was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MEST) (No. 2008–0061908), the Korean Research Foundation Grant funded by the Korean government (KRF-2012-001400).

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