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Application of neuro-fuzzy PID controller for effective post-chlorination in water treatment plant

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ABSTRACT

The presented chlorine controller system has neglected the travel time for monitoring the amount of chlorine in water treatment plant (WTP). In the present study, an adaptive neuro-fuzzy inference system was used to predict the travel time and chlorine changes that take place at a clear well in a typical WTP. The artificial Neuro-Fuzzy Inference System combined with Proportional Integral Derivative (PID) controller system was applied to optimize the chlorine dosing rate and to minimize the chance of errors. The travel time and the dosing rate were automatically calculated and injected using the proposed model and the controller. The standard deviation of an output chlorine rate was 3.6 and 7 times less than those of an old controller system in real application and in simulation, respectively. It was found that the neuro-fuzzy PID controller made a significant contribution to supply hygienically safe drinking water by considering various conditions including the travel time than the existing methods.

Keywords: Neuro-fuzzy PID; Post-chlorination; Chlorine dosing rate; Water treatment plant

1. Introduction

Drinking water can be contaminated by regrown microorganisms when the injected chlorine concentration fails to maintain the required concentration throughout the entire water treatment plant (WTP). Chlorine is the most commonly used disinfectant due to its ease of application and monitoring, its low cost, and its effectiveness in killing bacteria [1–3]. Most of the WTPs in Korea apply chlorine as a disinfectant. There are three types of chlorine injecting methods such as pre-chlorination, post-chlorination, and re-chlorination. In post-chlorination, chlorine is injected after the filtration process to keep the residual chlorine from being contaminated by various types of microorganisms. When the chlorine concentration is lower than the required value, drinking water can be easily contaminated by re-grown microorganisms. On the other hand, overdischarged chlorine concentration may create taste and odor problems. Maintaining chlorine level at the required value throughout the water treatment process is a crucial factor to overcome the above-mentioned problems.

In WTPs, the chlorine dosing rates are usually determined by the technical operators who are in charge of monitoring the input and output chlorine rates. In practice, however, it is not easy to adhere to

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the monitoring of chlorine dosing rates all day long and the dosing rates can vary depending on each operator's personal inclination. An automatic control of these chlorine dosing rates is required to overcome these difficulties.

The simplest model for chlorine decay is the first-order decay, one in which the chlorine concentration is assumed to decay exponentially [4–6] and for a given initial concentration and temperature, the first-order model can provide a fair approximation. Difficulties may arise in the decision process of decay constant and in the implementation of multiple experiments, as the results can be varied based on the quality of source water, temperature, Reynolds number, and the material properties of water pipes. As an alternative method, statistical models can be used. Unlike the first-order decay model, such statistical methods do not have to decide the constant. But they need large amounts of reliable data stored in a database to predict the amounts of residual chlorine.

Development of the statistical based models is necessary when the parameter estimation within the process-based model is imprecise or difficult to obtain [7]. It is also proper to study such models when the data required for the development of first order models are not available. This data-driven method does not require any prior knowledge of chemistry or mathematics related to residual chlorine [8]; but it is very important to find related variables to predict the residual concentration accurately. The control system in most of the WTPs in Korea is computerized to monitor and control each unit process, and to accumulate large amount of data on hard disk drives. These accumulated data are to be used to analyze the chlorine decay and to determine the most appropriate injection rate.

The overall objective of this study was to develop a control system for maintaining the output chlorine rate at one of the WTPs in Korea. The travel time at a water reservoir must be predicted to identify the chlorine decay. The chlorine dosing rate shall then be determined from the predicted chlorine decay with travel time. Statistical algorithms such as linear regressions, neural networks [9–11] and support vector regressions [12–14] can generally be used for modeling the chlorine decay and travel time. In the present study, Artificial Neuro-Fuzzy Inference System (ANFIS) was adopted due to its capacity to handle non-linearity, large amounts of data, and its fault and noise tolerances. Other learning algorithms were also used to compare them with the ANFIS. As all the learning algorithms are based on the feed-forward

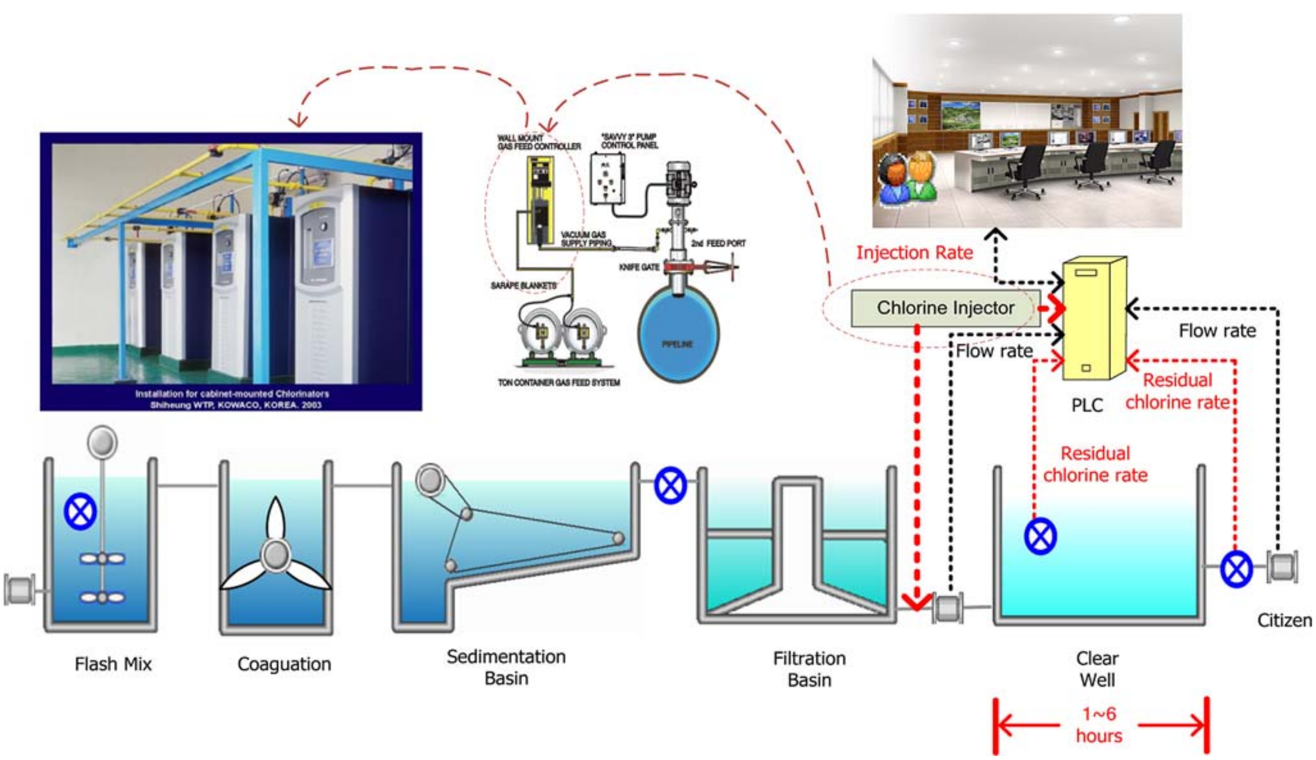

Fig. 1. The schematic diagram of a typical WTP in Korea.

controls, they may create errors. Proportional Integral Derivative (PID) as a conventional control algorithm was additionally applied to remove the errors in the output chlorine concentration [15] in the present study.

2. Learning algorithm

Fig. 1 shows the schematic diagram of a typical WTP in Korea. Untreated raw water is treated by several unit processes such as rapid mixing, flocculation, sedimentation, filtration, and chlorination in sequence. At the post-chlorination stage, chlorine is injected after the filtration process and some of the chlorine gets evaporated while going through the clear well. The evaporation rate must be estimated to inject the exact amount of the dosage rate.

In the present study, among several existing algorithms ANFIS was adopted as a learning algorithm as it is easy to implement. It also operates well using a small number of rules compared to other neural networks [14]. ANFIS is known as one of the methods to organize the fuzzy inference system with the given input–output data pairs. The parameters of consequent parts can be optimized using the least square method while the premise parameters using the steepest descent method. It is assumed that the fuzzy inference system has two inputs, x, y and one output z.

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

A detailed description of an ANFIS structure is summarized in Fig. 2. A square node (adaptive node) has parameters, while a circle node (fixed node) has none. The node functions in the same layer are of the same family function as described in Fig. 2:

Layer 1: Every node i in the first layer is an adaptive node with node function as shown in Eq. (1).

$$O_i^1 = \mu A_i(x) \tag{1}$$

where x is the input node i and A_i is the linguistic label (small, large, etc.). In other words, O_i^1 is the membership function of A_i and it specifies the degree to which the given z satisfies the quantifier A_i. A bell-shaped function was used as shown in Eq. (2).

$$\mu A_i(x) = \exp\left\{-\left(\frac{x - c_i}{a_i}\right)^2\right\} \tag{2}$$

Here $\{a_i, c_i\}$ is the parameter set. The parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a fixed node labeled $\prod$, which multiplies the incoming signals and sends the product out as shown in Eq. (3). For instance,

$$W_i = \mu A_i(x) \times \mu B_i(y),\ i = 1, 2 \tag{3}$$

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed one labeled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths as shown in Eq. (4):

$$\overline{W_i} = \frac{W_i}{W_1 + W_2} \tag{4}$$

For convenience, outputs of this layer are to be called normalized firing strengths.

Layer 4: Every node i in this layer is an adaptive node with the node function as shown in Eq. (5).

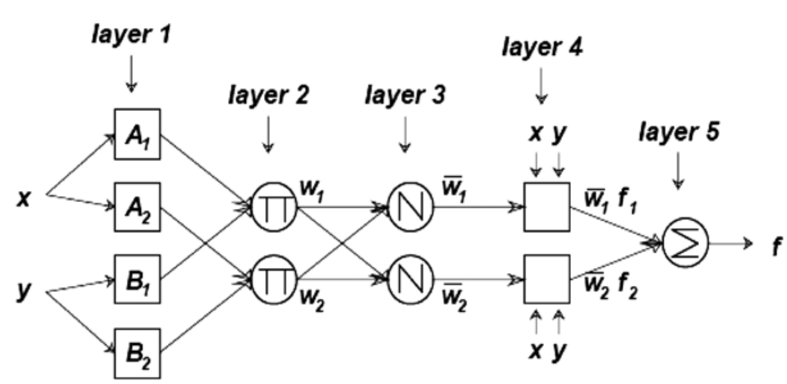

Fig. 2. A detailed description of an ANFIS structure.

$$O_i^4 = \overline{W_i}(p_i x + q_i y + r_i) \tag{5}$$

Here $\{p_i, q_i, r_i\}$ is the parameter set. The parameters in this layer are to be referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled C that computes the overall output as the summation of all incoming signals as shown in Eq. (6),

$$O_i^5 = \text{overall output} = \sum \overline{W_i} \times f_i = \frac{\sum w_i \times f_i}{\sum w_i} \tag{6}$$

The premise and consequent parameters can be chosen to minimize the following sum of the squared error as shown in Eq. (7).

$$E = \sum_{m=1}^{N} (T_m - O_m)^2 \tag{7}$$

Here, T_m is the desired output of mth data and O_m is the output of fuzzy model using the mth data, and N is the total number of training data sets. The steepest descent method as in a neural network can be applied to find the premise parameters and the least square estimate can be applied to optimize the consequent parameters [15].

3. Case study

3.1. Target plant and present controller

A case study was drawn up with one of the WTPs in Korea. The flowrate of this treatment plant was found to be 414,000 m^3/day. The chlorine dosing rate should be properly controlled to maintain the required output chlorine concentration. The chlorine dosing rate in this treatment plant was calculated using the following Eq. (8):

$$\begin{aligned} U_k = {} & (\text{In\_Cl}_2 - \text{Sed\_Cl}_2) + (\text{Desired\_In\_Cl}_2 \\ & - \text{ln} - \text{Cl}_2)^* \text{k}p_1 + (\text{Desired\_Out\_Cl}_2 \\ & - \text{Out\_Cl}_2)^* \text{k}p_2 \end{aligned} \tag{8}$$

In Eq. (8), sedimentation chlorine (Sed_Cl_2) was considered for the feed-forward control, which has affected the injection rate based on its residual. The value of (Desired_In_Cl_2—In_Cl_2)* kp_1 was updated every 20 min and that of (Desired_Out_Cl_2—Out_Cl_2)* kp_2 was updated every 120 min due to its delayed time. Here, the final goal is to maintain the Desired_Out_Cl_2. To achieve this goal, Desired_In_Cl_2 must be changed according to the amount of chlorine decay. But the amount of chlorine decay is not considered in Eq. (8) and Sed_Cl_2 should be carefully considered, because it also has a delayed time.

3.2. Post-chlorination design procedure

The dosing rate of post-chlorination was randomly determined by the desired input chlorine rate based on the operator's personal experience. In this case, the operator decides the desired input chlorine according to the output chlorine. The output chlorine is affected by the travel time. Although the output chlorine is highly affected by its decay, this process does not have an algorithm to calculate the travel time, which is one of the key factors of a chlorine decay. The treatment plants operator usually decides the desired input chlorine rate without the thoughtful consideration of travel time.

The crucial factor for the effective control of post-chlorination is the modeling of travel time as accurate as possible and the calculation of chlorine decay with time. Once the chlorine decay is predictable, it is easy for the controller to decide the ideal input chlorine rate. Fig. 3 shows the design procedure of an ANFIS PID controller. Initially the travel time is acknowledged by the filter output flow, storage tank output flow, and tank level. Once the travel time is given, chlorine decay in the storage tank is estimated by the travel time and water temperature. Then the input chlorine rate can be calculated by the sedimentation output chlorine and dosing rates. Finally, the dosing rate is determined by the sedimentation output chlorine and desired input chlorine rates considering the decay.

3.3. Plant controller and modeling

Pearson's correlation coefficient was used for the variable selections. And the variables for chlorine decay were analyzed as follows.

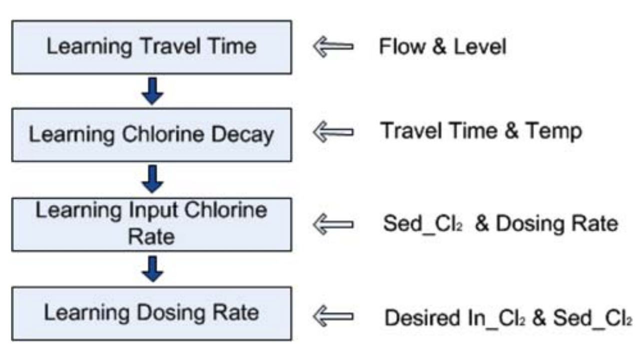

Fig. 3. The design procedure of an ANFIS PID controller.

Table 1
A comparison of the various learning algorithms

	NN(BP)		ANFIS		LR		SVR	
	Train	Test	Train	Test	Train	Test	Train	Test
Mean absolute percentage error (MAPE) (%)	7.24	8.35	7.84	8.13	8.15	8.79	8.59	8.41

Pearson's correlation coefficients by the variables were given as follows:

- Input and output chlorines = 0.914
- Travel time and (input–output) chlorine = 0.166
- Water temp and (input–output) chlorine = 0.093

According to the above-mentioned analysis, the output chlorine was found to be influenced by the input chlorine predominantly. The chlorine decay was influenced by the travel time and temperature. The decay should be considered to obtain the exact output. As the travel time changes frequently, the desired input chlorine rate must be flexible according to the variation of time. In case of temperature, it follows the seasonal variation and does not require the chlorine rate in real time. Neural networks and regression methods can predict the output according to their status with other algorithms. The applied algorithm is selected to consider its error and to implement it easily. Table 1 summarizes the comparison of various learning algorithms.

As a result, the neural network has shown better results in the training data than the checking ones. The checking data have shown a slight overfitting. The ANFIS has shown better results in training data compared to linear regression (LR) and support vector regression (SVR), and its checking data have displayed the best fitting among them. The ANFIS with fuzzy C-means clustering can also reduce the number of rules, which can make its implementation easier due to the small number of estimated parameters. The ANFIS was eventually selected as the model algorithm for the process.

3.4. Modeling and controller

Optimization of modeling and controller are based on a large number of accumulated data from the WTP. Modeling was implemented by one of the learning algorithms from an uncontrollable environment and controllable input/output chlorine rate. The controller was implemented using the neuro-fuzzy inference system with a PID controller. Fig. 4 shows the schematic diagram of modeling and controller for the overall system. It would help to simulate post-chlorination process to decide the optimized dosing rate.

As the sedimentation residual chlorine and dosing rates are inputted into model 1, it gives the value of the input chlorine concentration rate. In this case, the target input chlorine level did not reach because it was affected by the changes in its environment such as the input flow and sedimentation chlorine. Feedback controller is to be added to remove the probable error. In model 2, the output chlorine concentration is mainly influenced by the input chlorine. But the differences between the input and output chlorines were caused by the travel time and water temperature. Their relationships were modeled using the neuro-fuzzy inference system. It would be helpful to estimate the output chlorine rate according to the

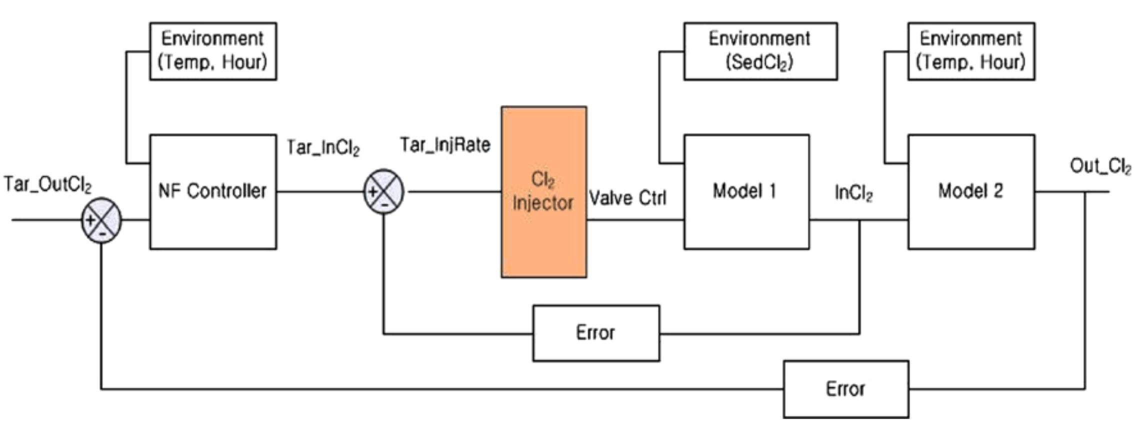

Fig. 4. Modeling and controller of overall system.

Table 2
Calculating procedure for the delay time between the injection and measurement points

Sampling pump	20 L/min (roughly)
PVC line diameter	25 mm
PVC line distance	70 m
PVC water quantity	$\pi \times r^2$=3.14 × (12.5/1,000)^2 = 0.00049 m^3/m = 0.49 L/m
Total water quantity	0.49 L/m × 70 m = 34 L
Pipe delay	Total water/sampling pump = 34 L/(20 L/min) = 1.7 min
Delay time	Pipe delay + Water tank delay = 1.7 min + 3 min ≈ 5 min

delay should be carefully decided. Input sampling time was calculated by the procedure shown in Table 2. The delay time should be more than 5 min to match the dosing rate and its influence.

The time between input and output chlorine rates changes continually and the output PID control period must be more than the maximum delay time – 5 h as shown in Fig. 5.

4. Results and discussion

4.1. Simulation

It is essential to collect the tremendous amounts of data to effectively analyze the post-chlorination process. Eight kinds of variables were considered such as sedimentation chlorine, input chlorine, output chlorine, travel time, water temperature, level, and input variables such as input chlorine, travel time, and water temperature.

The ANFIS controller provides the desired input chlorine and dosing rates to keep the output chlorine concentration constant, despite the changes in its variable. The characteristics of instruments, injectors, and other environments, however, can be changeable with time and produce various types of errors. In the present study, two sets of PID controllers were adopted to compensate the target input chlorine and dosing rates to overcome such offsets. Both of input and output chlorine concentrations having a long time

Table 3
Percentage of error for the travel time estimation with the selected variables

Variables	MAPE (%)
Level, effluent flowrate	9.3
Level, effluent flowrate, travel time (n−1)	9.1
Level, effluent flowrate, differential level	9.2
Level, effluent flowrate, effluent differential flowrate	9.6
Level, influent flowrate, effluent flowrate	8.1

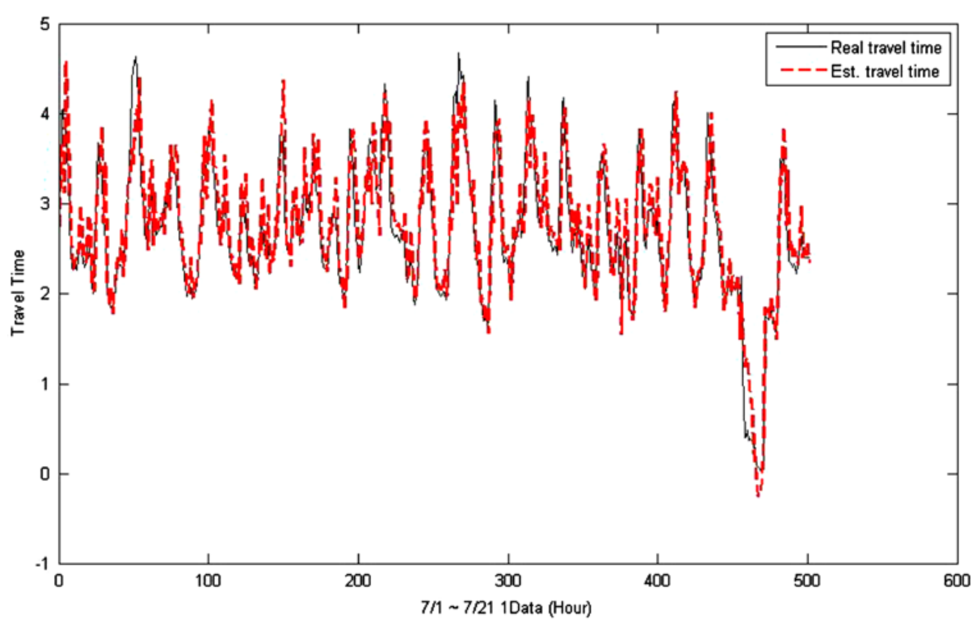

Fig. 5. Comparison of estimate and real travel times.

and output flows. Most of the information on the variables was collected using the K-water's database gathered from more than 30 WTPs in Korea. Roughly 4,500 h of recorded data from the 1st day of January to the 21st day of June were used for the simulation.

Table 3 shows the percentage of error for the travel time estimation with the selected variables. Here, the value of level was taken from the storage tank level, while the differential level from the hourly level difference. The value of an effluent differential flowrate was also taken from the hourly effluent flow difference, while the value of influent flowrate from the storage influent. The travel time has shown the optimum value when the level, influent flowrate, and effluent flowrate were considered.

The estimated travel time was found to be similar to the real one as shown in Fig. 5. Although the travel time changes from 0 to 5 h, it goes well along with its changes. In fact, the travel time can be estimated by the prediction of algorithm considering relevant variables.

The percentage of error for output chlorine estimation with the selected variables is summarized in Table 4. The estimation was found to be better in case of considering the input chlorine concentration, travel time, and water temperature. Its error has shown to be lower than 2.16%, which means that the output chlorine can be modeled by these variables.

The estimated and real output chlorine rates were compared as shown in Fig. 6. Although the estimated output chlorine rate was deviated in the upper and lower parts compared to the real one, it fitted well.

Table 4
Percentage of error for output chlorine estimation with the selected variables

Variables	MAPE (%)
In_Cl_2, Travel time	2.21
In_ Cl_2, Travel time, Water temp.	2.16

Fig. 7 shows the output chlorine rate by the present controller. There was a great variation in the output chlorine rate. Although the target output chlorine rate was 0.75 mg/L, it ranged from 0.65 to 0.82 mg/L.

Fig. 8 shows the variation in the input and output chlorine rates by the proposed ANFIS combined with the PID controller. Its simulated output chlorine rate was in the range of 0.75 mg/L, which was the target to reach. The input chlorine rate varies from 0.78 to 0.9 mg/L, while the output rate ranges from 0.723 to 0.766 mg/L. Its variation was found to be smaller than the one compared to the previous controller.

Table 5 shows the simulation results of three controllers. The neuro-fuzzy and two PID controllers have the least error compared to the other ones. The percentage error of ANFIS and two PID was less than half compared to the one of only-ANFIS controller. The ANFIS combined with two PID controller systems was adopted to control post-chlorination process in this study.

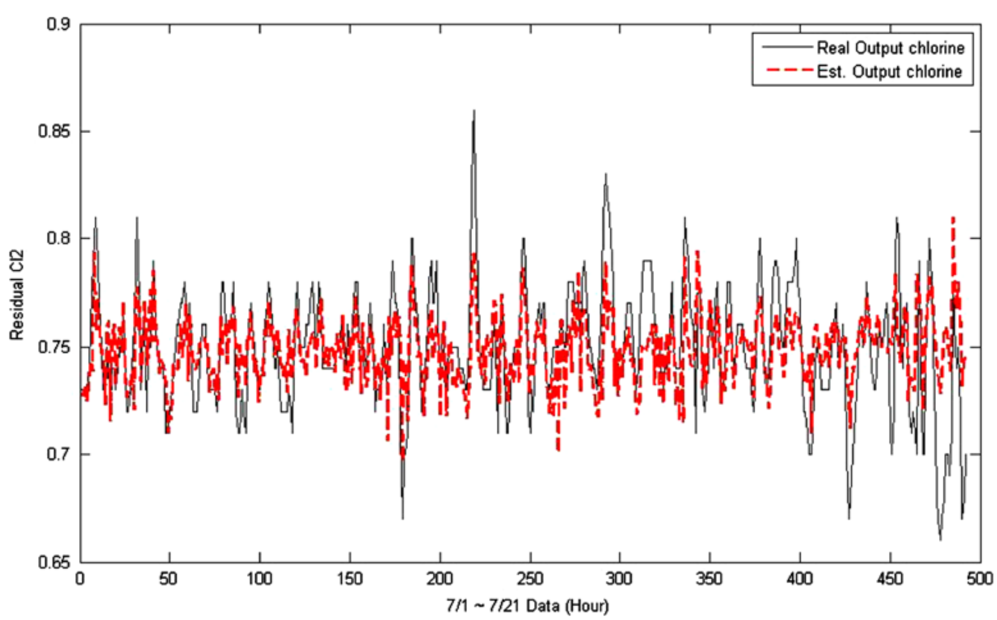

Fig. 6. Comparison of estimate and real output chlorines.

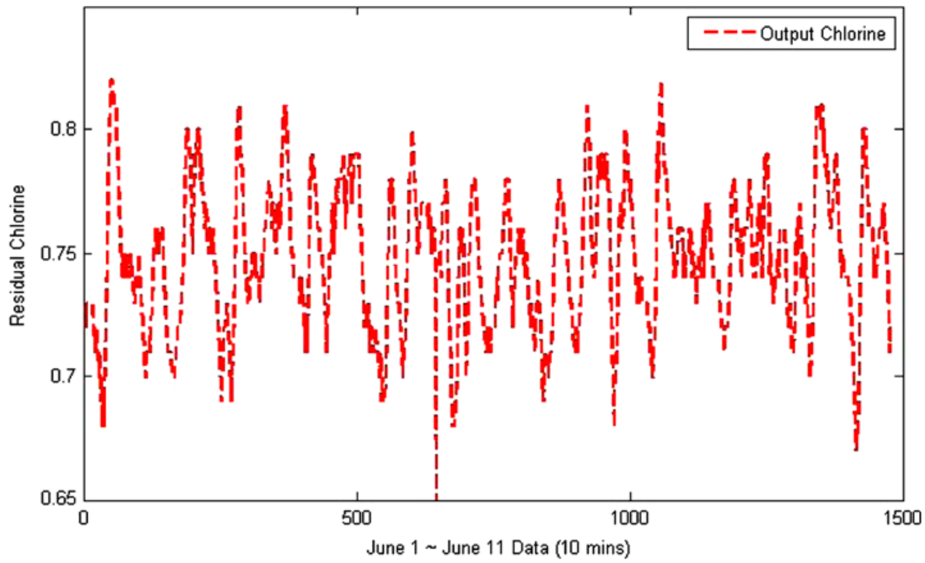

Fig. 7. Output chlorine rate by present controller.

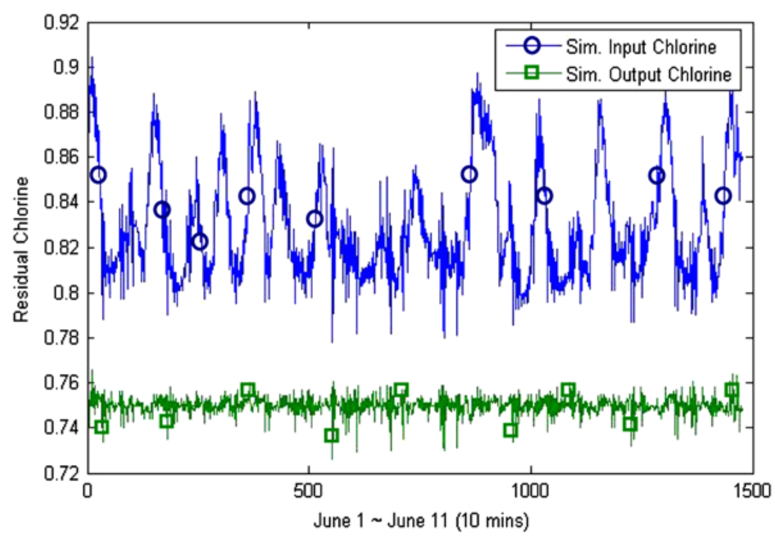

Fig. 8. Variation of input and output chlorine rates by the proposed ANFIS and PID controller.

Table 5
Simulation results of three controllers

Variables	MAPE (%)	
	In_Cl_2	Out_Cl_2
ANFIS only	0.81	0.77
ANFIS + PID (In_Cl_2)	0.31	0.62
ANFIS + PID (In_Cl_2) + PID(Out_Cl_2)	0.34	0.35

Table 6
A comparison of the standard deviation for the old and new controllers in simulation

Old controller		New (proposed) controller	
Mean	SD	Mean	SD
0.746	0.0286	0.75	0.0038

The output chlorine using the conventional controller varies from 0.65 to 0.82 mg/L, while the new controller ranges from 0.723 to 0.766 mg/L. The major difference comes from the fixation of travel time. As

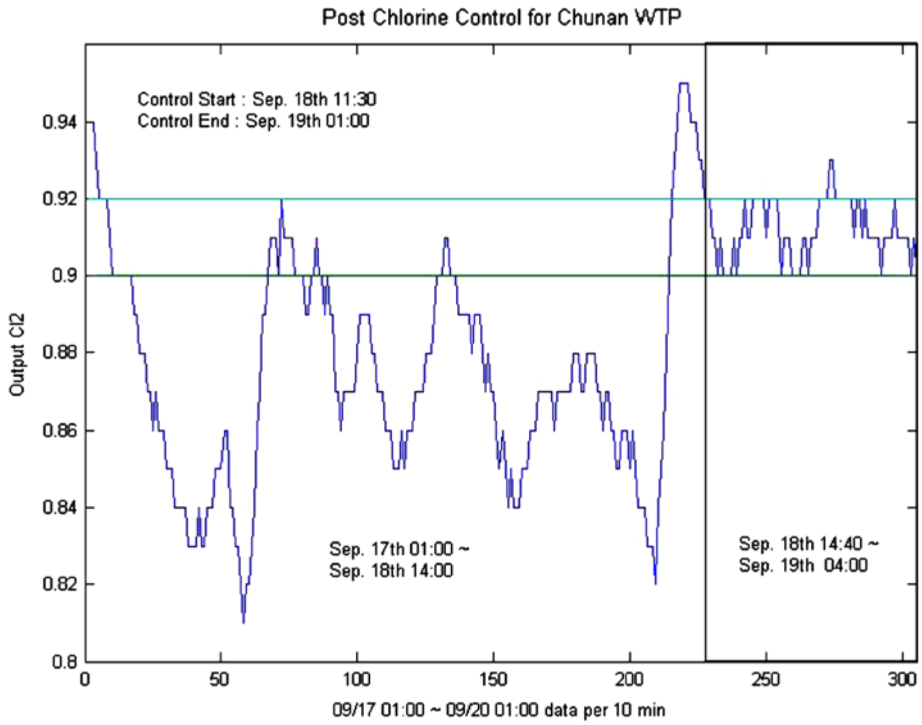

Fig. 9. Real output residual chlorine by old and new controller.

the input chlorine rate of the proposed controller changed by travel time estimated by the neuro-fuzzy model, the output chlorine rate kept constant as shown in Fig. 8. It was found that the PID controller has contributed to minimize the variation of desired output chlorine rate by compensating the error. A comparison of the standard deviation for the old and new controllers in simulation is tabulated in Table 6. It was found that the ANFIS combined with two PIDs system has shown seven times lower standard deviation than the conventional types of controllers. The chlorine output rate can be more stable by applying this system.

4.2. Experiment

The new control input was made from 11:40, on 18 September to 01:00, on 19 September. The output results were obtained 3 h later due to the delay time and the real results were displayed from 14:40, on 18 September to 04:00, on 19 September. Experimental section was divided into two – before and during experiments. Fig. 9 shows the real output residual chlorine by old and new controllers. At that time, the target output chlorine concentration increased up to 0.9 mg/L due to the hot temperature in summer season. The proposed controller kept its output chlorine rate lower than 0.02 mg/L, while the variation of old controller is great.

Table 7
Standard deviation of old and new controllers in experiment

Old controller		New (proposed) controller	
Mean	SD	Mean	SD
0.875	0.029	0.912	0.008

The standard deviation of an old controller is as high as 0.029, while the new controller was deviated by 0.008 as shown in Table 7. It means that the output chlorine rate can be improved once the travel time is estimated and the optimal dosing rate is decided using neuro-fuzzy algorithm.

In the case of a conventional controller, the outputs were so deviated because they did not care for the travel time. But the new controller decided the desired input chlorine rate based on its travel time, and most of the output data ranged from 0.90 to 0.92 mg/L. It looks well controlled. The mean of "during the experiment" had an error from its desired output of 0.9 mg/L. It was caused by the learning data set, which was not considered until 23 August, and its surrounding environment changed slightly. To compensate this fact, PID error compensation equation should be applied for the desired input chlorine as shown in Eq. (9).

$$\text{Error} = \frac{1}{n}\sum_{i=1}^{n}(\text{Des\_Out\_Cl}_2 - \text{Out\_Cl}_2) \tag{9}$$

The output chlorine rates are expected to move around the desired output.

5. Conclusions

The operator in the treatment plant randomly decides the desired input chlorine rate as the current chlorine controller system did not make any thoughtful consideration of the travel time. The chlorine dosing rate entirely relied upon the operator's experience. In this study, the ANFIS combined with a PID controller system was applied to optimize the chlorine dosing rate. The travel time and dosing rate were automatically calculated and injected using the proposed model and controller. The standard deviation of output chlorine rate was 3.6 and 7 times less than old controller in real application and in simulation, respectively. As the travel time in WTP changes continually, the learning algorithm such as neuro-fuzzy inference system is recommended to be adopted to supply hygienically safe drinking water.

References

[1] V.K. Chambers, J.D. Creasey, J.S. Joy, Modeling free and total chlorine decay in potable water distribution-systems, J. Water Supply Res. Technol. Aqua 44(2) (1995) 60–69.

[2] F. Hua, J.R. West, R.A. Barker, C.F. Forster, Modelling of chlorine decay in municipal water supplies, Water Res. 33(12) (1999) 2735–2746.

[3] L. Kiene, W. Lu, Y. Levi, Relative importance of the phenomena responsible for chlorine decay in drinking water distribution systems, Water Sci. Technol. 38(6) (1998) 219–227.

[4] A. Jadas-HeÂ cart, A. Morer, A. Stitou, P. Bouillot, The chlorine demand of a treated water, Water Res. 26 (1992) 1073–1084.

[5] G.R. Zhang, L. Kiene, O. Wable, U.S. Chan, J.P. Duguet, Modelling of chlorine residual in the water distribution network of Macao, Environ. Technol. 13 (1992) 937–946.

[6] L.A. Rossman, R.M. Clark, W.M. Grayman, Modelling chlorine residual in drinking water distribution systems, J. Environ. Eng. 120 (1994) 803–820.

[7] M.J. Rodriguez, J.R. West, J. Powell, J.B. Serodes, Application of two approaches to model chlorine residuals in Severn Trent Water Ltd (STW) distribution systems, Water Sci. Technol. 36(5) (1997) 317–324.

[8] J.B. Serodes, M.J. Rodriguez, A. Ponton, Chlorcastc: A methodology for developing decision-making tools for chlorine disinfection control, Environ. Model. Softw. 16(1) (2001) 53–62.

[9] Ethem Alpaydin, Introduction to machine learning, The MIT Press, Cambridge, 2004, pp. 229–251.

[10] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning internal representations by error propagation, Cogn. Sci. 1 (1985) 4–8.

[11] F. Rosenblatt, Principles of neurodynamics: Perceptrons and the theory of brain mechanisms, Spartan, New York, NY, 1962.

[12] V. Vapnik, S. Golowich, A. Smola, Support vector method for multivariate density estimation, In: Advances in Neural Information Processing Systems, vol. 12, MIT Press, Cambridge, MA, 1999, pp. 659–665.

[13] Christopher M. Bishop, Pattern Recognition and Machine Learning, Springer, Cambridge, 2006, pp. 325–344.

[14] Joao P. Ferreira, Manuel M. Crisostomo, A. Paule Coimbra, SVR versus neural-fuzzy network controllers for the sagittal balance of a biped robot, IEEE Trans. Neural Networks 20(12) (2009) 1885–1897.

[15] J.-S.R. Jang, ANFIS: Adaptive network based fuzzy inference system, IEEE Trans. Syst. Man Cybernetics 23(3) (1993) 665–685.