Application of Neuro-Fuzzy PID Controller for Post Chlorine Process

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Abstract: Drinking water can be contaminated by microorganisms which can be re-grown in case of not controlling chlorine concentration well in water treatment plant (hereafter WTP). It can be harmful to public health. Most WTPs have used chlorine as disinfectant. It can be used in pre-chlorination, post-chlorination and re-chlorination. In post-chlorination, it is injected after filtration to keep residual chlorine from being contaminated by microorganisms. Post-chlorine process without re-chlorination is directly serviced to citizens. If the concentration is low, drinking water can be contaminated by bacterial re-growth. On the other hand, the high chlorine can lead to customer complaints about taste and odor. Therefore, it is necessary to predict chlorine decay in clear well to maintain desired chlorine levels. In this paper, it is shown that artificial neuro-fuzzy inference system could be used to model chlorine decay in the process and control residual chlorine better than present controller, in which cascade control is considered to compensate the error in the output.

Keywords: Post-chlorination, Neuro-Fuzzy inference system, Chlorine decay

I. INTRODUCTION

A major objective of drinking water treatment is to provide microbiologically safe drinking water. Water contaminated by microorganisms can be a major risk to public health. 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].

Usually, chlorine dosing rate is determined by operator by monitoring input and output chlorine rate in WTP. However, it is hard to concentrate on the process all day long among many processes and the rate is usually fixed, which doesn't guarantee the output chlorine to be as we wish. Therefore, it is necessary to predict the proper rate based on reliable data to ensure pleasant drinking water.

The simplest model for chlorine decay is the first order decay model 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. The difficult problems are to decide the decay constant and carry out many experiments that can vary with the quality of the source water, the water temperature, the Reynolds number and the material properties. These kinds of works are based on a high level of knowledge of the chlorination process. First order decay with respect to chlorine [7] :

$$dC/dt = -kC \text{ or } C_t = C_0 \exp(-kt) \qquad (1)$$

Where k is the first order decay constant.

As an alternative, statistical models can be used. Unlike first order decay model, it is not necessary to decide the constant and take experiment. Instead, it requires much reliable data stored in a database to predict residual chlorine. The development of statistically based models for disinfection control purposes is proper in cases where parameter estimation within the process-based model is imprecise or difficult to obtain [8] or where the data required for the development of first order models are not available. This data driven method doesn't require a prior knowledge of chemistry and mathematics related to residual chlorine [9]. It is very important to find related variables to predict residual concentration well. Most WTPs are computerized to monitor and control their processes and then to accumulate huge amounts of data in hard disk drives. These large amounts of data can be used to analyze chlorine decay and to determine proper injection rate. The following figure demonstrates water treatment plant and detailed post-chlorination process.

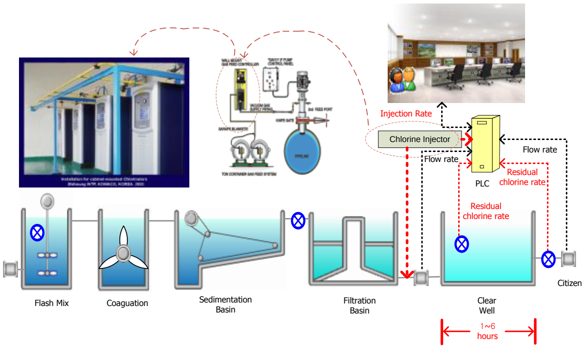

Fig. 1. Conventional Water Treatment Process

II. CASE STUDY

1. Object WTP

The case study considers chlorine decay and residuals in the Cheonan WTP, Cheonan, Korea. This treatment has a capacity of 414,000 m^3/day and has served citizens living in North Cheoung-cheong province since December, 2003.

2. Research Procedure

The most important item in controlling post-chlorine is to model travel time as accurately as possible and to know the decay according to time. If chlorine decay is predicted, it is easy for the controller to decide desired input chlorine. In the following figure, design procedure is introduced.

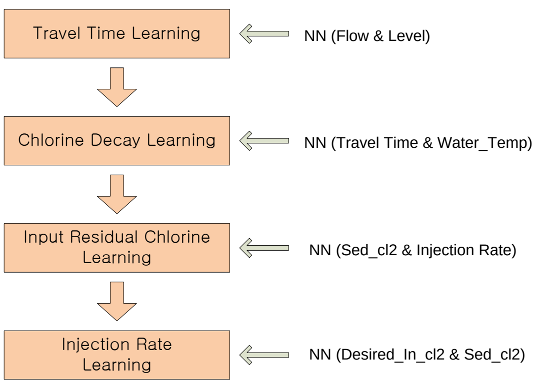

Fig. 2. Design Procedure

3. Comparison of Learning Algorithm

There are many learning algorithms which can predict output according to states. Applied algorithm is selected considering error and easy implementation. Test result is as follows:

Table 1 Comparison of Learning Algorithm

	NN(BP)		ANFIS		LR		SVR	
APE (%)	Trn.	Chk.	Trn.	Chk.	Trn.	Chk.	Trn.	Chk.
	7.24	8.35	7.84	8.13	8.15	8.79	8.59	8.41

As a result, neural network (back propagation) has the best result only in training data but its check data isn't best. It appears slightly over fitted. ANFIS has better result in training data compared to LR and SVR, and its check data has the best result. Also, ANFIS with fuzzy C-means clustering can reduce the number of rules which make implementation easier. Thus, ANFIS is selected as modeling algorithm for the process.

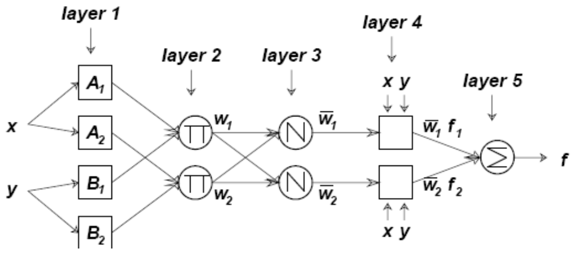

Fig. 3. ANFIS Structure

Layer 1 : Create fuzzy set with proper function

$$O_i^1 = \mu A_i(x) \tag{2}$$

$$\mu A_i(x) = 1/\{1 + \left(\frac{x-c_i}{a_i}\right)^{2b_i}\} \tag{3}$$

Layer 2: Multiply the incoming signals and send the product out.

$$w_i = \mu A_i(x) \times \mu B_i(y), i = 1, 2 \tag{4}$$

Layer 3: Normalize the weight

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \tag{5}$$

Layer 4: Compute the result of each node

$$O_i^4 = \bar{w}_i\,(p_i x + q_i y + r_i) \tag{6}$$

Layer 5: Compute the overall output as the summation of all incoming signals

$$O_i^5 = \text{overall output} = \textstyle\sum_i \bar{w}_i \times f_i = \frac{\sum_i w_i \times f_i}{\sum_i w_i} \tag{7}$$

The premise $[a_i, b_i, c_i]$ and the consequent parameters $[p_i, q_i, r_i]$ can be chosen to minimize the following sum of squared error by least square estimate [10].

$$\boldsymbol{E} = \sum_{m=1}^{N} (\mathbf{T_m} - \mathbf{O_m})^2 \tag{8}$$

III. RESULTS

1. Simulation

The following figure is the proposed structure to model and control post-chlorination process.

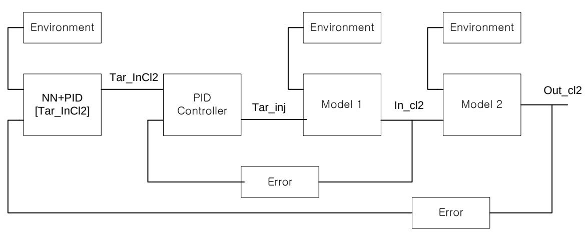

Fig. 4. Modeling and Controller

At first, its variables are chosen by the use of correlation coefficient and prominent component analysis. All of modeling is based on neuro-fuzzy inference system. If the system gives desired input according to states, PID controller try to get rid of its error. Other PID controller is used for cascade control, because this process has very long delay time. The result of simulation is as follow.

A. Modeling

- Estimate of travel time

Table 2 Error according to Selected Variables

Variables	APE
Level, Out_flow, Travel Time(n-1)	9.1%
Level, Out_flow, Level_dot	9.2%
Level, Out_flow, Out_flow_dot	9.6%
Level, Fil_flow, Out_flow	8.1%

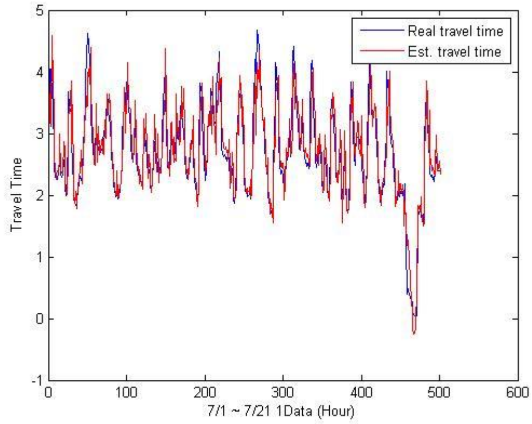

Fig. 5. Estimate Result of Travel Time

- Estimate of Out_cl2

Table 3 Error according to Selected Variables

Variables	APE
In_cl2, Travel time	2.21%
In_cl2, Travel time, Water temp	2.16%

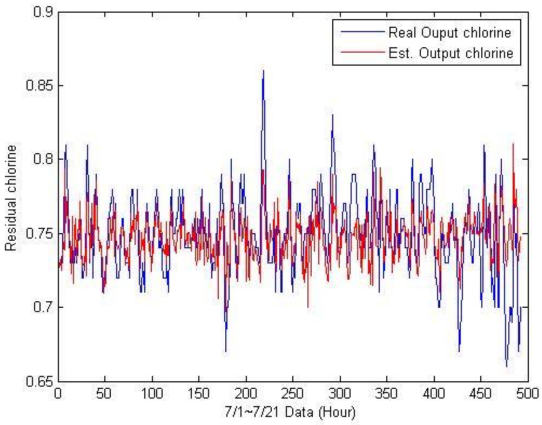

Fig. 6. Estimate Result of Output Chlorine

B. Controller

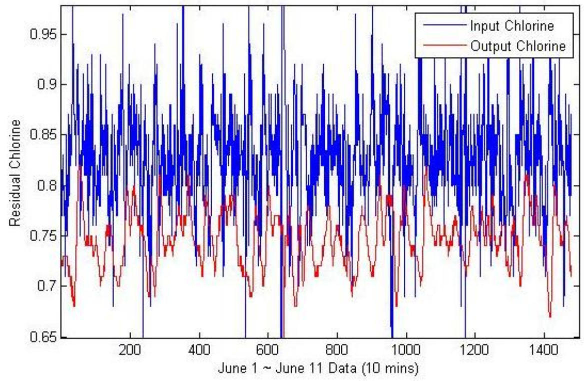

Fig. 7 Old Controller

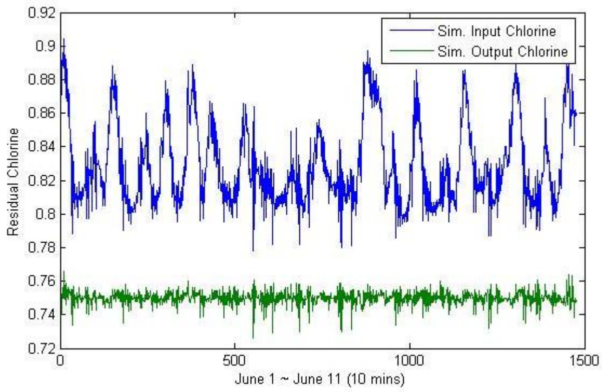

Fig. 8. New NF+PID Controller

Table 4 Comparison of Controller

Old Controller		New Controller	
Mean	STDEV	Mean	STDEV
0.746	0.0286	0.75	0.0038

C. Simulation result

Given the above figures, the output chlorine by old controller varies from 0.66mg/L to 0.82mg/L but new controller ranges from 0.723mg/L to 0.766mg/L. The major difference is whether travel time is fixed or not. While input of old controller is not changed a lot, neuro-fuzzy system helps to calculate the desired input chlorine in real time. Additionally, PID controller would help to keep the desired output chlorine by controlling the offset.

2. Experiment

Control input given by neuro-fuzzy system was given from Sep 18 11:40 to Sep 19 01:00. Its output result would be affected 3 hours later owing to its delay at that time. Then, its real result is from Sep 18 14:40 to Sep 19 04:00. Before new input was given, sedimentation chlorine became fixed not to affect the output, and delay time became shorter from 30 to 5 minutes to get quick feedback. The experiment could be divided into 3 sections, which are before experiment, during experiment and after experiment.

- Before experiment : Delay time =30min, Gain=0.5, Sedimentation chlorine considered.
- During experiment: New input by neuro-fuzzy, Delay time =5min, Gain=0.5, Sedimentation chlorine not considered.
- After experiment: Delay time =5min, Gain=0.5, Sedimentation chlorine considered.

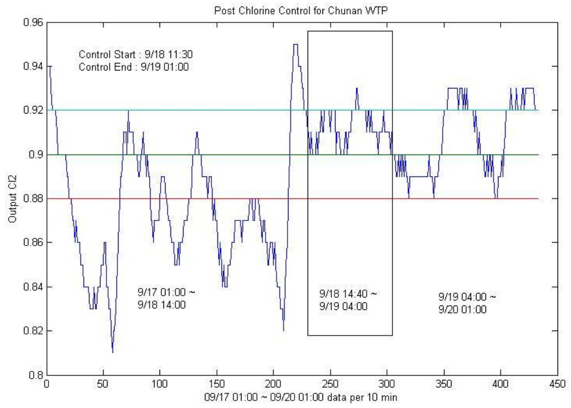

Fig. 9 Experiment result

Table 5 Experiment Result

Before Exp.		During Exp.		After Exp.	
Mean	STDEV	Mean	STDEV	Mean	STDEV
0.875	0.029	0.912	0.008	0.907	0.016

A. Experiment result

In the "before experiment" section, its outputs are deviated because it doesn't consider travel time and sedimentation chlorine. In "During experiment," new desired input chlorine is set according to its travel time and most output data are located from 0.90 to 0.92mg/L. It looks well controlled. Besides, the mean of "during experiment" has an error from its desired output 0.9mg/L. The result is that training data set is considered until August 23th and its environment is changed a little. To compensate for this, the following equation would be applied to desired input chlorine as a bias.

$$Bias = 1/\mathrm{n}\sum_{i=1}^{n} \left(Des\_Out\_cl2_i - Out\_cl2_i\right) \quad (9)$$

Output chlorine rates are expected to move around its desired output.

IV. CONCLUSION

Present chlorine controller doesn't consider travel time in real time until now, which usually relies on operator's experience. It is supposed to be difficult to change it in real time. Here, travel time is calculated by neuro-fuzzy inference system. Even though it has some errors, output chlorine becomes much better than before. Its boundary becomes much shorter. It is expected to help to drink water with more pleasant characteristics.

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