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Predicting real-time coagulant dosage in water treatment by artificial neural networks and adaptive network-based fuzzy inference system

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A B S T R A C T

Coagulation is an important component of water treatment. Determining the optimal coagulant dosage is vital, as insufficient dosage will result in unqualified water quality. Traditionally, jar tests and operators' own experience are used to determine the optimum coagulant dosage. However, jar tests are time-consuming and less adaptive to changes in raw water quality in real time. When an unusual condition occurs, such as a heavy rain, the storm water brings high turbidity to water source, and the treated effluent quality may be inferior to drinking water quality standards, because the conventional operation method can be hardly in time to adjust to the proper dosage. An optimal modeling can be used to overcome these limitations. In this paper, artificial neural network (ANN) and adaptive network-based fuzzy inference system (ANFIS) models were used to model poly aluminum chloride (PAC) dosing of northern Taiwan's surface water. Each of them was built based on 819 sets of process-controlled data. The performance of the models was found to be sufficient. Two simulation tools, ANN and ANFIS, were developed that enabled operators to obtain real-time PAC dosage more easily. The self-predicting model of ANFIS is better than ANN for PAC dosage predictions.

1. Introduction

The treatment of drinking water provides multiple barriers to protect public health by removing microorganisms and chemicals that may cause illness to consumers. The removal of turbidity and color to produce water that is aesthetically acceptable to consumers is a very important component of water treatment. Water treatment consists of a sequence of complex physical and chemical processes; currently, in many water treatment plants (WTP), process control is generally accomplished through examining the quality of the product water and adjusting the processes through an operator's own experience and jar tests. This practice is inefficient and slow in controlling responses. With more stringent requirements being placed on water treatment performance, operators needed a reliable tool to optimize the process controlling in WTP. Much of the difficulty in modeling water treatment processes can be related to complex interactions among many influential water quality factors, and many chemical and physical reactions. In modeling water treatment processes, the major challenge is to establish the nonlinear relationships between the inputs and outputs of each process. In this paper, one such tool is presented, which is a process control system built with the artificial neural network (ANN) modeling or adaptive network-based fuzzy inference system (ANFIS) modeling approach.

The coagulation process is the most important in WTP. The coagulant of WTP in this study is poly aluminum chloride (PAC). Traditionally, optimum coagulant dosages are determined using jar tests. However, jar tests are relatively expensive and time-consuming. Consequently, jar tests are generally only carried out periodically (Yu et al., 2000), which means that they are reactive, rather than proactive, as coagulant dosage is continuously changing when responding to the occurrence of water quality problems. In addition, as a result of the amount of time it takes to conduct jar tests, they cannot be used in responding to rapid changes in raw water quality (Joo et al., 2000), and thus are not suitable to real-time control (Yu et al., 2000).

In some previous studies, ANNs were used to develop process models for simulating the alum dosing process. For example, Zhang and Stanley (1999) and Baxter et al. (1999) developed ANN models for predicting treated water turbidity and color, respectively, at the Rossdale WTP in Edmonton, Alberta, Canada. Gagnon et al. (1997) developed an ANN model for predicting the optimal alum dosage for the Ste-Foy WTP in Quebec, Canada. Joo et al. (2000) developed a similar model for Chungju WTP in Korea, and van Leeuwen et al. (1999) developed an ANN model for the prediction of optimal alum dosage based on jar tests conducted on surface waters collected in southern Australia. Holger et al. (2004)

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used the same database as van Leeuwen et al. (1999) to predict optimal alum dosage and treated water quality parameters. Deveughele and Do-Quang (2004) developed SUEZ ENVIRONNEMENT, which was built by self-organizing features map and multi-layer perceptron (MLP), to predict the optimal coagulant dosage in the WTP, which is located at Viry in the vicinity of Paris. Bae et al. (2006) developed the model in which the coagulant type was determined by decision tree rules and dosage was estimated by neural network models that perform mapping between the water quality (e.g. pH, turbidity, alkalinity, water temperature, etc.) and coagulants (e.g. PAC, PASS and PSO-M). Chen and Hou (2006) developed a practical feedforward control system with fuzzy feedback trim, which is presented for controlling the coagulant dosage strategy of the Changhsing Water Purification Plant of Taipei Water Department. Benardos and Vosniakos (2007) developed a methodology for determining the best architecture that is based on the use of a genetic algorithm (GA) and the development of novel criteria that quantify an ANN's performance (both training and generalization) as well as its complexity.

In all of the above studies, the model inputs consisted of raw water parameters, whereas the model output was the optimal alum dosage needed to achieve the desired treated water quality. Zhang and Stanley (1999) included the turbidity of the treated water as an input in addition to a number of raw water quality parameters in their ANN model for predicting the optimal alum dosage at the Rossdale WTP. Yu et al. (2000) did the same in their model for the prediction of optimal alum dosage at a WTP in Taipei City, Taiwan. Chun et al. (1999) used the ANFIS for coagulant dosing process in a water purification plant.

In all of the above studies, the raw water quality was more stable, not changing, e.g. when an unusual condition occurs, such as a heavy rain, the storm water brings high turbidity to water source. Otherwise, when influent water does not provide information on water quality, the predicting model cannot be used. Based on these concepts, a project was initiated to study the potential capacity of ANN and ANFIS process control in WTP. This study was conducted at the WTP in Taipei County, Taiwan, having a water purification capacity of 1,200,000 CMD. The objective of this study was to select a section of the water treatment processes, collect real operational data, build, and test the ANN and ANFIS predicting model. The treatment processes include the coagulation, flocculation, sedimentation, filtration, and disinfection process (Fig. 1).

In this paper, the principal concepts of using the ANN and ANFIS in the water treatment modeling and process control are introduced. The ANN and ANFIS focus on finding a repeated, recognizable, and predictable pattern(s) between the causes and the effects from the past operation data records. The ANN and ANFIS modeling approach does not require a description of how the processes occur in either the micro- or macro-environments, but only the knowledge of important factors that governed the process. This situation makes the ANN and ANFIS modeling approach a rational choice for process modeling and controlling in water treatment. Once reliable ANN and ANFIS process models are developed, it can be integrated into a process-controlled architecture.

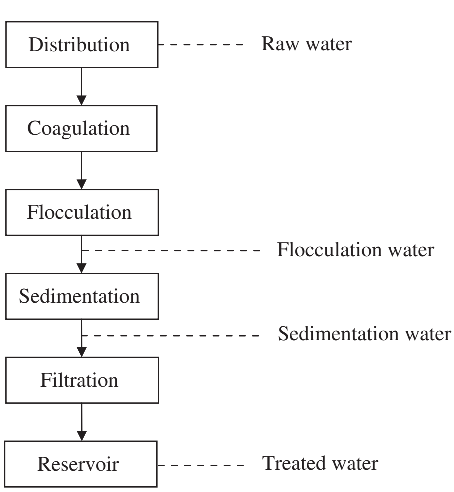

Fig. 1. The WTP in Taipei Country, Taiwan Layout.

2. Methodology

2.1. Data collection

In this research, both ANN and ANFIS models that were developed are capable of assisting treatment plant operators with determining real-time PAC dosage for WTP in Taipei County, Taiwan. The WTP in this study is a conventional treatment facility consisting of coagulation, flocculation, sedimentation, and filtration.

In order to obtain the input/output data required to develop and validate ANN and ANFIS models, water samples were collected from WTP in Taipei County, Taiwan. The desired water quality parameters were measured, including the turbidity, pH, color, and temperature of each raw, flocculation, sedimentation, and treated water (Table 1).

2.2. The index

Inputs to the model predicting PAC dosage parameters were the water quality parameters of each process in a WTP and prior PAC dosage. The model output was the PAC dosage. The input parameters include the PAC dosage of yesterday, PAC dosage before yesterday, and the temperature, turbidity, color, pH in each of the raw, flocculation, sedimentation, and treated water. The input parameters were decided on the Pearson factor (r) with the real-time PAC dosage:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{\left[n\sum x^2 - (\sum x)^2\right]\left[n\sum y^2 - (\sum y)^2\right]}} \tag{1}$$

where n is the number of data, x, y are the values of parameters. In this study, x was the input parameter and y was the output parameter. The Pearson factor of each input and output was calculated as shown in Table 2.

A root-mean-square normalized error (RMSE) is used as a performance index to compare the prediction capability of ANN trained by each data set. The RMSE is known to be descriptive when the prediction capability among predictors is compared (Zurada, 1992):

$$\mathrm{RMSE} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(o_\mathrm{p} - o_\mathrm{d})^2} \tag{2}$$

where n is the number of data, o_p is the predicted value and o_d is the real operating value.

The correlation coefficient (R^2) indicator compares the performance of the model with that of a naive benchmark model, the output of which is the mean of all samples (Baxter et al., 1999). It can therefore be used to compare the relative performance of the models for different model outputs.

2.3. ANN model

The 819 data points were divided into two subsets using the method proposed. These subsets are: (i) a training set for