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Adaptive Modeling and Classification of the Secondary Settling Tank

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Abstract−In biological wastewater treatment plants the biomass is separated from the treated wastewater in the secondary settler; thus, efficient operation of the secondary settler is crucial to achieving satisfactory effluent quality in the wastewater treatment process (WWTP). In the present work, system identification and soft-computing techniques were used to formulate a model for predicting the solid volume index (SVI) and classification of the sludge bulking phenomenon in the settler. An adaptive time series model was applied to predict the SVI of the secondary settler; this model uses the recursive least square (RLS) method to update the model parameters. The method for classifying the current state of the secondary settler is based on the strong correlation that was observed between the settler state and the values of the time series model parameters, which enabled the time series model parameters to be used as effective features for monitoring the secondary settler. To classify the current state of the secondary settler, a neural network (NN) was used to classify the adaptive time series model parameters, where a hybrid Genetic Algorithm (GA) was used to decide the number of hidden nodes of the NN classifier. Application of the proposed method to a full-scale WWTP demonstrated the utility of the method for simultaneously predicting the SVI value of the secondary settler and classifying the current state of the settler.

Key words: Auto-regressive Exogenous (ARX) Model, Bulking, Genetic Algorithm (GA), Neural Network (NN) Classifier, Recursive Least Square (RLS) Method, Solid Volume Index (SVI)

INTRODUCTION

Increasingly stringent environmental regulations demand ongoing improvements in the quality of the effluent from wastewater treatment plants. Achieving better effluent quality requires improved modeling and control of plant performance. The first step in any procedure aimed at reducing the pollutant level in effluent from the biological wastewater treatment process (WWTP) should be to model and analyze the current state of each unit of the WWTP. The recovery of the WWTP from a 'bad' state to a 'normal' state is slow; hence, good modeling and status classification in the biological process are crucial to the process efficiency because they allow corrective action to be taken well before the onset of a dangerous situation [Olsson and Chapman, 1988; Hasselblad et al., 1996; Teppola et al., 1997, 1999; Lee et al., 1998; Rosen and Olsson, 1998; Van Dongen et al., 1998; Bang et al., 2001; Choi et al., 2001; Yoo et al., 2000, 2001, 2002].

The activated sludge process (ASP) is the most extensively used process in wastewater treatment plants. In the ASP, wastewater containing organic matter, suspended solids, and nutrients enters an aerated tank where it is mixed with biological floc particles. The mixture is held in the tank for a predetermined contact time, after which it is discharged into a settler that separates the suspended biomass from the treated water. Most of the biomass is recirculated to the aeration tank, and a small amount is purged daily (Fig. 1). The ASP is a complex biological process that is difficult to fully understand and therefore difficult to operate and control. Both the quantity and quality of the inflow vary with time. In addition, the system contains a living catalyst (the microorganisms), and the microorganism population varies over time both in quantity and in the relative populations of different species. Knowledge about the process is scarce because the few available on-line analyzers are unreliable, and most existing data related to the process is subjective and cannot be numerically quantified. The majority of the problems associated with poor effluent quality from the ASP result from the inability of the secondary settler to efficiently remove the suspended biomass from the treated water. When the biomass is heavily colonized by long filamentous bacteria, which hold the flocs apart, sludge settling is hindered and the solid volume index (SVI) increases. This phenomenon is referred to as bulking [Belanche et al., 2000].

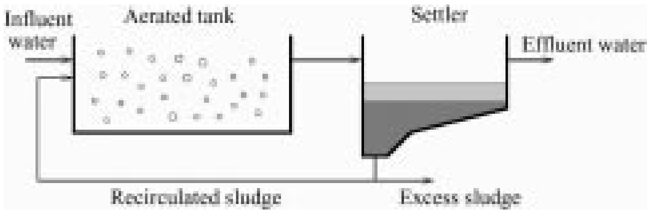

Fig. 1. A basic activated sludge process with an aerated tank and a settler.

Sludge bulking is perhaps the most common cause of ASP failures (i.e., exceeding the permitted discharge levels). It has been estimated, for example, that over 50% of the treatment plants in the world regularly experience bulking conditions. Bulking slows the settling in the settler and, as a consequence, solids in these conditions are more likely to escape the separation unit. Recent efforts to understand the factors that lead to bulking have relied primarily on experimental observation of the bacterial species involved. Uncer-

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tainty regarding the factors that trigger bacterial growth is a major obstacle to the elucidation of the problem. However, the factors causing the bacterial growth have been established only in a few cases, and even in these cases the experimental results are open to contradictory interpretations. As a result, no models have been established for the analysis and prediction of bulking conditions. In particular, no deterministic mathematical models have been formulated to predict the behavior of filamentous organisms [Capodaglio et al., 1991; Belanche et al., 2000].

As mentioned above, the performance of the secondary sedimentation in the WWTP is crucial to the operation of activated sludge systems. The operation of the secondary settler depends on the status of the sludge, which in turn relies on a variety of parameters such as the temperature, organic loading, influent flow rate and floc properties. In the present study the solid volume index (SVI) is used to represent the bulking condition; it is easily measured and provides a good estimate of the settling properties of a sludge. In addition to being routinely collected at the majority of wastewater treatment plants, the SVI has the advantage that it provides a measure of bulking that is not associated with any particular species in the system. Therefore, the SVI describes the bulking situation regardless of the population differentiation and dynamics of the system biomass [Tcholanoglous and Burton, 1991]. High SVI values are indicators of a bulking state and excessive numbers of filamentous microbes, which is one of the major upsets of the ASP leading to the deterioration of the purification efficiency. On the other hand, the secondary settling tank itself evolves over time as the biomass adapts to different conditions. The ability to predict the time evolution of the SVI value is very important to the effective operation of the settler.

The development of a model that can predict with reasonable accuracy the dynamics of the secondary settler, and that can predict the appearance of sludge bulking, is of great practical importance. Such a prediction model should accurately predict the SVI of the mixture in the secondary settler based on the most relevant variables of the process, such as flow rates, temperature and biomass concentration.

In the present study, system identification and soft-computing techniques were used for the modeling and classification of the contents of the secondary settling tank. The SVI of the secondary settler was forecast by using the recursive least squares (RLS) method. We verified that the RLS model parameters provide a good modeling of the secondary settler by observing the evolution of the RLS model parameters through a power spectrum analysis. Finally, we proposed a scheme for monitoring the secondary settler by using a neural network (NN) classifier combined with the adaptive processing scheme. The proposed method is shown to be suitable for application to the full-scale WWTP.

METHODS

In this section we propose a system for monitoring the secondary settler. The first subsection explains the use of time series modeling to predict the SVI value and power spectrum analysis to verify the classification capability, while the second subsection provides a description of the NN classifier that is used to identify the current state of the settler. The genetic algorithm used to design the NN structure is introduced in the third subsection, and a proposed hierarchical structure is described in the final subsection.

1. Time Series Modeling

To model SVI of the secondary settler, we apply the system identification methods, where the autoregressive exogenous (ARX) model is used [Ljung, 1987; Ko and Cho, 1996]. A general form of the discrete ARX model is as follows.

$$\begin{aligned} &y(t)+a_1y(t-1)+\Lambda+a_{n_a}y(t-n_a)\\ &\quad=b_1u(t-1)+b_2u(t-2)+\Lambda+b_{n_b}u(t-n_b)+e(t) \end{aligned} \tag{1}$$

where a_i and b_i are coefficients, n_a and n_b are model orders, y(t) is a process output, u(t) is a process input, and e(t) is an unmeasured white noise. The objective of the ARX model is to estimate the adjustable parameters of a_i and b_i to minimize the difference between the predicted process output and the measured process output. Because the secondary settler is a time varying process and has inherently dynamic characteristics, it is required to use the adaptive capability. For this purpose, we use the with recursive least square (RLS) algorithm that makes the modeling technique well-suited for time varying environment.

The RLS algorithm is as follows.

$$\begin{aligned} &\hat{\theta}(t)=\hat{\theta}(t-1)+K(t)(y(t)-\hat{y}(t))\\ &\hat{y}(t)=\varphi^T(t)\hat{\theta}(t-1)\\ &K(t)=\frac{p(t-1)\varphi(t)}{\lambda+\varphi^T(t)P(t-1)\varphi(t)}\\ &P(t)=\frac{P(t-1)-\dfrac{P(t-1)\varphi(t)\varphi^T(t)P(t-1)}{\lambda+\varphi^T(t)P(t-1)\varphi(t)}}{\lambda} \end{aligned} \tag{2}$$

where K(t) is a adaptation gain, θ(t) is a parameter vector, $\hat{y}(t)$ is a prediction value based on observations at time t−1, φ(t) is a regression vector, λ is a forgetting vector, and P(t) is a covariance matrix of estimates. This recursive form is very convenient for updating the model at each time, so that the model follows the gradual change in the characteristic of the settling process. If the ARX model parameters are well tuned, a change in dynamic characteristics of the settling process will cause gradual change in the parameter vector and prediction error. Therefore, the status of the settler can be observed by a gradual change in the ARX model coefficients.

In order to see the sensitivity of the ARX coefficients at each state and verify its discriminant ability, a comparison of the power spectrum at each state is required. The power spectrum of a stationary process is defined as the Fourier transform of its covariance function [Ljung, 1987]. While a deterministic signal can be expressed as a mixture of sine and cosine functions at different frequencies, a time series response or stochastic system response of a function of time does not belong to the class of functions dealt with in the usual Fourier transform theory. The frequency decomposition of these random functions can be obtained by taking the Fourier Transform of the auto-covariance function for which the usual Fourier transform can be used.

For a stochastic process, y(t) can be given by

$$y(t)=G(q)u(t)+H(q)e(t) \tag{3}$$

where u(t) is a quasi-stationary, deterministic signal with a spectrum, and e(t) is white noise with a variance. Let G(q) and H(q) be stable filters. Then y(t) is quasi-stationary and

$$\Phi_y(\omega)=|G(e^{iw})|^2\Phi_u(\omega)+\sigma_a^2|H(e^{iw})|^2 \quad (4)$$

$$\Phi_{yu}(\omega)=G(e^{iw})\Phi_u(\omega) \quad (5)$$

where $\Phi_y(\omega)$ is a power spectrum of y(t) and $\Phi_{yu}(\omega)$ is a cross spectrum of y(t) and u(t). It should be noted that these types of spectrum estimates are inherently smooth because they are obtained based on a parameter representation of the system. The result has a physical interpretation, where $|G(e^{iw})|^2$ is the steady-state amplitude of the response of the system to sine wave with a frequency. The value of the spectral density of the output is then the product of the power $|G(e^{iw})|^2$ and the spectral density of the input $\Phi_u(\omega)$. If the power spectrum is separated and has a dissimilarity value at a different state, analyzing the power spectrum of the ARX coefficients can make the decision on the state of the secondary settler.

2. Pattern Classification (Neural Network)

While different states are not completely separable in the original input and output dimensional space under a wide range of conditions, the classes can become separable in the dimensional feature of the ARX parameters space. Here, the ARX coefficients are used as input features for NN classifier which has the ability of nonlinear mapping.

Pattern recognition methods such as multiplayer perceptron (MLP) and radial basis function (RBF) have been known as an important technique for the classification problems because they do not require accurate process models which are often difficult to obtain for many biological and chemical processes. And the computing ability of neural network outperforms the conventional statistical approach in many engineering application because of its non-linear transformation [Bishop, 1995; Lin and Lee, 1996; Haykin, 1999; Himmelblau, 2000].

A neural network maps a set of input patterns (*e.g.*, process operating conditions) to respective output classes (*e.g.*, categorical groups). We use an input vector (x) and an output vector (y) to represent the input pattern and output class, respectively. The output vector, y, from NN is bipolar, with −1 indicating that the input pattern is not within the specific, and 1 indicating that it is within a specific class (*e.g.*, "−1"=not in class I; "1"=in class I). The actual output from NN is a numerical value between −1 and 1, and can be viewed as the probability that the input pattern corresponds to a specific class. The output vector (y) contains three possible classes: y={class I, class II, class III}. Note that for every point within the input space, there must be only one class specified. In this paper, we have only three possible output vectors for training the network, for example, y={[1, −1, −1], [−1, 1, −1], [−1, −1, 1]}.

After the calculation of NN output, the values of output nodes are passed to the maximum selector. The output node selected by the maximum selector gives information on the class that includes a current input. In theory, for an M-class classification problem in which the union of the M distinct classes forms the entire input space, we need a total of M outputs to represent all possible classification decisions, as depicted in Fig. 2. In this figure the vector x_j denotes the *j*th prototype (i.e., unique samples) of an *m*-dimensional random vector x to be classified by a NN classifier. It can be expressed as follows:

$$\text{If } y_i(x_j)>y_k(x_j) \text{ for all k (k=1, 2, …, M: k}\neq\text{i) , then } x_j\in s_i \quad (6)$$

where x_j is *j*th input vector, y_i is the *i*th output node value of NN classifier for input x_j, s_i is the *i*th state of secondary clarifier, and M is the number of output nodes. A unique largest output value exists with probability 1 when the underlying posterior class distributions are distinct [Haykin, 1999].

3. Genetic Algorithm (GA)

GA is a derivative-free stochastic optimization technique in which the stochastic search algorithm is based on the idea of the principle of natures such as natural selection, crossover, and mutation. GA has largely been used in two major parts: optimization and machine learning. GA is a probabilistically guided optimization technique. Unlike other classical optimization techniques, GA does not rely on computing local derivatives to guide the search process. One of the GA's characteristics is the multiple points search, which discriminates GA from other random search methods and helps GA avoid getting trapped in local minima. Hence, GA reveals its full power when applied to very complex problems [Goldberg, 1989; Wang et al., 1998].

Recently, GA has been successfully applied to WWTP for estimating water quality model parameters, water quality parameters in a water quality modeling framework, calibrating rainfall-runoff models, solving ground water management problems, and sizing water distribution networks [Mulligan and Brown, 1998].

Since the ultimate objective of a pattern classifier is to achieve an acceptable rate of correct classification, this criterion is used to judge when the variable parameters of NN are optimal. But the size of a hidden layer is a fundamental question often raised in the application of NN to real-world problems. The exact analysis of this issue is rather difficult because of the complexity of the network mapping and the nondeterministic nature of many successfully completed training procedures. Hence, the size of a hidden layer is usually determined experimentally.

This paper focuses on the application of GA as an important tool in the structure and parameters learning of NN. Structure and parameter learning problems of NN are coded as genes (or chromosomes) and GA is used to search for better solutions (optimal structure and parameters). Here, the string of chromosomes represents the number of hidden layers of NN. GA typically starts by randomly generating an initial population of strings. Each string is transformed into the fitness value to obtain a quantitative measure. On the basis of the fitness value, the strings undergo genetic operations. The goal of genetic operations is to find a set of parameters that search the optimal solution to the problem or to reach the limited generation. The basic concept behind this technique comes from that a complete set of weights is coded in a binary or decimal string, which has an associated "fitness" indicating its effectiveness [Lin and Lee, 1996].

4. Hierarchical Structure

The system proposed for monitoring the secondary settler is composed of three fundamental parts. Fig. 3 presents a schematic diagram of the proposed hierarchical structure. First, an adaptive mod-

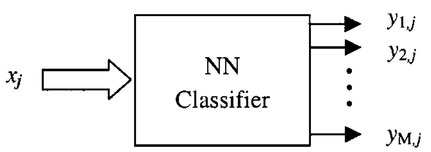

Fig. 2. Block diagram of a pattern classifier.

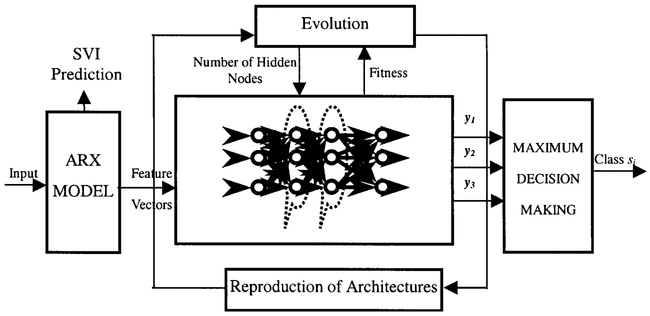

Fig. 3. Schematic diagram of the proposed hierarchy structure.

el is used to predict the SVI value and provide a classifier with feature vectors. This step utilizes the ARX model to predict the SVI value in the secondary settler, where the model parameters are adaptively estimated by the RLS method, and the ARX model parameters are used as the input vector of the NN classifier. Second, an NN classifier is designed to identify the current state of the secondary classifier. After the NN is trained, the state class of the settler is chosen from the values of the recognized output nodes according to the maximum selection rule (i.e., a single value is chosen from the classifier output according to the rule "the minority is subordinated to the majority"). Third, the structure of the NN classifier is decided from the optimal number of hidden nodes by using a genetic algorithm.

RESULTS AND DISCUSSION

In this paper, we used the industrial wastewater treatment facility data of the iron and steel making plant in Korea. It is a general activated sludge process that has five aeration basins and a secondary settler. Fig. 4 shows the layout of the WWTP. It has two wastewater sources, where one directly comes from a coke making plant (called BET3) and the other comes from a pretreated wastewater of upstream WWTP at other coke making plant (called BET2). The coke-oven plant wastewater is produced during the conversion process of coal to coke in the steel making industries. It is extremely difficult to treat the coke wastewater because it is highly polluted and most of the chemical oxygen demand (COD) originates from large quantities of toxic, inhibitory compounds and coal-derived liquors (*e.g.* phenolics, thiocyanate, cyanides, poly-hydrocarbons and ammonium). The data set consist of daily mean values from January 1, 1997 to December 22, 1999. The data are divided into two parts. A training set consisting of the values during first two years and a test data set during the remaining one year are used to see how well the proposed algorithm works.

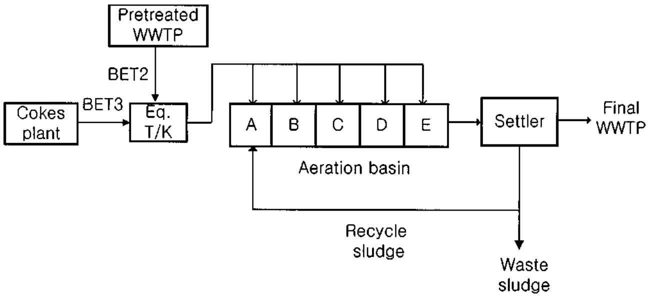

Fig. 4. Plant layout of WWTP.

First, the ARX model structure is as follows. Its inputs are four: the influent flow rate, influent COD, dissolved oxygen (DO) of the final aeration basin, and mixed liquor suspended solid (MLSS) in the final aeration basin. Output variable is SVI of the settler. The state of the secondary settler is divided three classes (normal, bad and bulking state) which are judged by an experienced operator. The ARX model is adapted by RLS method with the forgetting factor. At present there is no better method available to fundamentally determine the ARX model order. A most natural approach to search for a suitable ARX model structure is simply to test a number of different ones and to compare the resulting models. Time-lagged scheme is adopted because the settler is considered as a dynamic system (i.e., bacteria do not respond in a detectable manner to instantaneous inputs of measurable parameters), and therefore a time-lagged input scheme for the input parameters is deemed to reflect actual conditions within the secondary settler. Two days lag is chosen, which corresponds to the average hydraulic retention time of the system, that is, the order of each exogenous input is 2 and order of AR part is 3. The applied ARX model has a following form:

$$\begin{aligned} &y(t)+a_1y(t-1)+a_2y(t-2)+a_3y(t-3)\\ &\quad=b_{1,1}u_1(t-1)+b_{1,2}u_1(t-2)+b_{2,1}u_2(t-1)+b_{2,2}u_2(t-2)\\ &\qquad+b_{3,1}u_3(t-1)+b_{3,2}u_3(t-2)+b_{4,1}u_4(t-1)+b_{4,2}u_4(t-2) \end{aligned} \tag{7}$$

where y(t) is SVI, $u_1(t)$ is influent flow rate, $u_2(t)$ is influent COD, $u_3(t)$ is DO, and $u_4(t)$ is MLSS. To remove data redundancy, we normalize the raw training data. The RLS method uses the dead-zone method to remedy the estimation windup.

Fig. 5 shows the one-step ahead prediction result of SVI in the secondary settler during the test period. The dot point is real value and solid line is the prediction value. The result during the test period confirms the good prediction capability of the proposed method. In order to see the sensitivity of the ARX coefficients at each state, the parameter values of each state are shown in Fig. 6. In this Figure, the ARX model parameters have different values according to each state, which means that the state decision of the secondary settler can be achieved by quantitatively analyzing the ARX parameters. To confirm theoretically the difference between the ARX

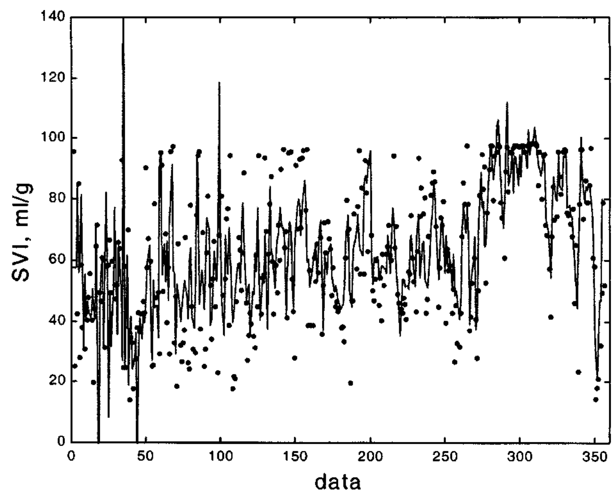

Fig. 5. One-step ahead prediction value of SVI using RLS method.

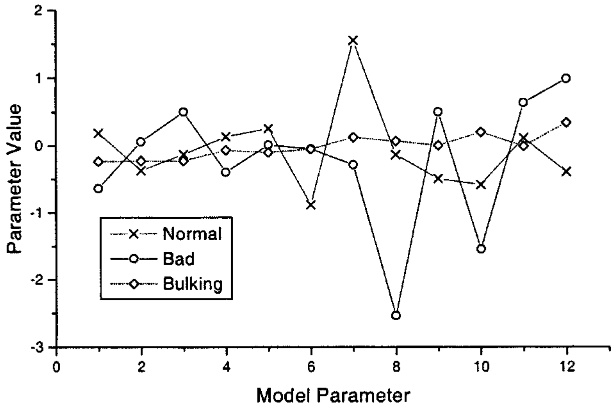

Fig. 6. Sensitivity of the ARX model parameters at each state.

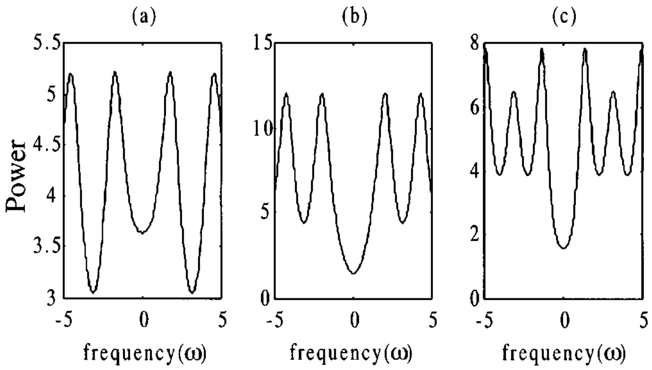

Fig. 7. Power spectrum in each state (a) normal (b) bad (c) bulking state.

parameters in each class, we display the power spectrum analysis of the ARX parameters in the Fig. 7, which shows the validity of the recognition system of the state in the settler.

Second, we use an MLP structure with two hidden layers as an NN classifier, where local features are extracted in the first hidden layer and global features are extracted in the second hidden layer [Haykin, 1999]. The number of the hidden layers is decided by the hierarchical GA. To speed up training and stabilize the learning algorithm, we use the momentum term, adaptive learning rate, normalized weight updating and batch learning techniques. MLP is trained by using three patterns according to the state of the secondary settler. The number of the ARX parameters, which is used as the input variables of MLP, is eleven. And other operating conditions, such as toxic occurrence, microorganism state and status of aeration basin can be taken as additional features to compensate for sensitivity of the ARX parameters to the variation of operation conditions. The classification rate for these additional features does not show any improvement. In this paper, for purposes of clarity, we do not use this additional information. The input features are normalized in [–0.9, 0.9] ranges in order to prevent saturation of an activation function. The corresponding target values of output nodes are set to normal state (0.9, –0.9, –0.9), bad state (–0.9, 0.9, –0.9), bulking state (–0.9, –0.9, 0.9) for each state of three classes. In the GA application of MLP structure, the initial population size of parents is 30 and generation number is 100. Ranked-base selection as a selection operator, and mutation and uniform crossover as a search operator are used. We have set the mutation rate for 0.01 and crossover rate for 0.6. GA finds the optimal number of each hidden node quickly, because the search space is small in the application. The number of first and second hidden layers is 7 and 4, respectively. In other simulations, MLP with two hidden layers shows better result than that with only one hidden layer.

Table 1. Confusion matrix of the test data

		Predicted		
		Normal	Bad	Bulking
Actual (Desired)	Normal	228	9	6
	Bad	36	59	17
	Bulking			0

In testing mode, the maximum value of NN classifier outputs is chosen in determining the present states. It indicates what state is the current state. The test data has not a bulking state but only the normal and bad state. Table 1 shows the confusion matrix representing classification results from the test set. This is a matrix whose *i* by *j* element indicates the number of samples that originate from the *i*th distribution and are classified into the *j*th state. The diagonal elements are the numbers of samples classified correctly, while the off-diagonals are the numbers of misclassified samples. Though output values do not completely agree with the corresponding desired outputs, they are reasonable to recognize the present state. From the NN classifier, the classification rate is about over 80.9% on an average, even though the settler was run under a wide range of operating conditions. Because the process has an abrupt load variation during the latter part of test set, the misclassification rate was higher in this period.

CONCLUSION

Recognition of the process state of the secondary settler enables effective decision-making in regard to the operation of the process, and consequently enhances the treatment efficiency. In the present study we formulated a model for the prediction and classification of the SVI values in the secondary settler. We verified that the hybrid structure of the ARX model and NN classifier could predict the SVI value and classify the current state of the secondary settler. The theoretical analysis revealed a strong correlation between the settler states and the values of the ARX parameters. The proposed method was shown to be capable of simultaneously predicting the SVI value of the secondary settler and classifying the current state of the secondary settler.

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