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PREDICTION OF SEWAGE QUALITY BASED ON FUSION OF BPNETWORKS

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Abstract-Sewage treatment system is a complicated nonlinear system with multi-variables, chemical reaction, biological process and altered loads, hard to describe mathematically. Thus prediction of the effluent quality parameters of sewage treatment plant has being a challenge. In this paper we adopt fusion of two BP networks to predict sewage quality parameters with a popular process Cyclic Activated Sludge System (CASS). We take use of SVM (support vector machine) to classify the input data into two kinds, and train the corresponding BP networks with the two kinds of data. Before using SVM to classify the input data, PCA (principle component analysis) is used to analyze the correlation between sewage quality parameters. Then we predict the value of sewage quality parameters with the fusion results of the two BP networks. Test results of the case study show that fusion of BP networks not only can improve the stability of BP networks but also can improve the prediction accuracy.

Index terms: sewage quality parameters, BP networks, SVM; fusion.

I. INTRODUCTION

With the development of environment protection, sewage treatment is becoming a hot issue. A great deal of methods for sewage treatments has been presented, and the CASS (Cyclic Activated Sludge System) is used universally. Since sewage treatment process is closely linked with sewage sources, chemical composition, flow rate, biological process conditions, and the recycle rate of the settled sludge, real-time monitor and control for better effluent quality has become increasingly challenging. Clearly, a precision prediction model of effluent quality is necessary for the sewage treatment system. It is also proved in some papers [3-5] that a precision prediction model of effluent quality is helpful to control a sewage treatment plant in real-time for better effluent quality effectively. For example, in [3] a prediction model of effluent flow cooperated into the sewage treatment plant control system determined the appropriate level of sewage treatment plant anaerobic storage tank, improved the efficiency of treatment. In [4] a prediction model of effluent quality acts as the identification model of controlled object in a sewage treatment control system, make the sewage treatment system controlled with high accuracy. Additionally, as a high energy consumption industry, the energy consumption of sewage treatment plant is concerned especially. According to sewage treatment process, energy consumption of sewage treatment plant can be categorized into three kinds, i.e. energy consumption of pretreatment, biological-chemical treatment process, and sludge treatment. Among the three kinds energy consumption, energy consumption of biological-chemical treatment process is the major part, which nearly accounts for 60% of the total energy consumption[7-8]. Energy consumption of biological-chemical treatment process has a close relation with sewage quality parameters. Predicting sewage quality parameters accurate and fast help to control aeration system automatically and reduce the energy consumption [9-13].

Among the effluent quality parameters, COD (Chemical Oxygen Demand) is important. Because it is a comprehensive indicator of the total amount of organic in sewage. The content of organic matter is one of the indicators for classifying the environmental quality of the natural water. It is also the bases for judging whether the water is polluted or not. BOD（Biochemical Oxygen Demand）is a comprehensive indicator about pollutants in sewage, such as organics. It is biochemical oxygen demand that is need when biological and chemical reaction of organics occurred. In this paper, we select COD and BOD as the sewage quality parameters to be predicted.

Methodology used in prediction of effluent quality of sewage treatment plant include ANN (Artificial Neural Network) [15-17] and SVM (Support Vector Machine) [3,4,6,18]. In [3], ANN is successfully used in the prediction of effluent flow. In [6], ANN is successfully applied in prediction of effluent quality of sewage treatment plant of SBR process through soft-sensor modeling method. But ANN has disadvantages of local minimum and dependency on learning sample numbers. SVM is a powerful machine learning method based on small sample statistical learning theory [1,2]. It adopts structure risk minimization principle which avoids local minimum and effective solves the over learning and assures good generalization and better predict accuracy. The special predominance of SVM in resolve limited samples, nonlinear function and multidimensional pattern recognition make it a powerful tools in prediction of effluent quality of sewage treatment plant. In[4], SVM is adopted to predict the effluent quality of a sewage treatment system of flocculation process. However, the SVM will be fail when some input data are missing. Except this, SVM does not have a general solution for nonlinear system.

In this paper we study the application of SVM and Bp network in prediction effluent quality of a sewage treatment with a CASS process, present a prediction method based on SVM and Bp network of CASS sewage treatment process. We use fusion of two BP networks to improve the stability and prediction precision of BP networks. We take use of SVM to classify the input data of BP networks. Before classifying, the outliers of the input data are deleted. In order to make SVM work more effectively, we analyze the influent quality parameters and parameter to be predicted with PCA (principle component analysis), get principle components, and choose the corresponding influent quality parameters that affected parameters to be predicted obviously. Then, we set up fusion of BP networks based on SVM, and train the networks with some data, and tested the networks with others, and fuse the results. The test result showed that the prediction method is effective that could predict the dynamic consumption during control process with high accuracy with high accuracy and quick learning speed.

II. SEWAGE TREATMENT PROCESS AND ITS'DIFFERENTIAL EQUATION MODEL

The sewage treatment process as shown in Figure1 mainly adopts cyclic active sludge to handle the influent sewage. The sewage firstly flows through coarse screen and fine screen, then into aeration tank meanwhile some active sludge are plunged into the tank and a blower blows oxygen necessary to reaction with active sludge into the tank. After the reaction is finished, sewage handled flows out through contact tank. Some quantity of sludge produced by the reaction goes back into aeration tank for reaction continually and others is discharged.

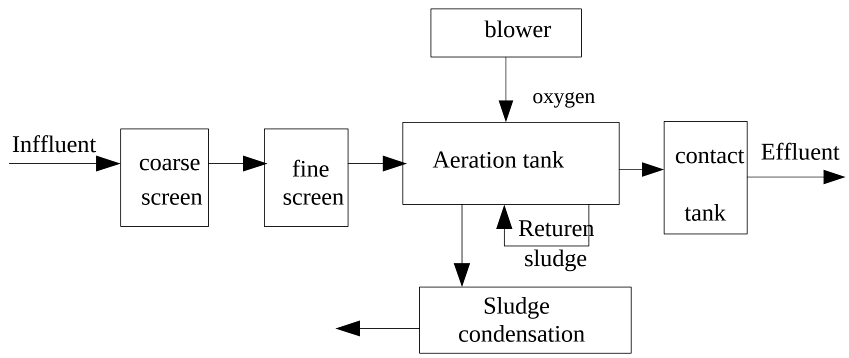

Figure 1. Block diagram of sewage treatment process

In view of the above process, according to the law of material balance, the following assumptions are made on the sewage treatment system of the activated sludge process[14]：

(1)Microorganisms are non-autotrophic microorganisms, and their growth rate is greater than the mortality rate, and their growth rate satisfies the Monod equation.

(2)No biochemical reaction occurred in the second sedimentation tank.

(3)Reflux sludge affect Influence of sludge age and yield coefficient.

(4)Biomass of influent is zero.

(5)Saturation constant of organic substrate KS<<Si

(6)Only study the nitration reaction of the system.

Under the above assumptions, the differential equation of the treatment process is shown as followed equation. The parameters in equation (1) see literature [19]. Obviously, the differential equation could not satisfy our requirement of predicting sewage quality parameters.

$$\begin{aligned}
&\frac{dSs}{dt}=\frac{q_F}{V}(S_{SF}-Ss)-\frac{\hat{\mu}_H}{Y_H}(\frac{Ss}{Ks+Ss})(\frac{So}{K_{OH}+So})X_H+(1-f_p)b_H X_H\\
&\frac{dS_O}{dt}=\frac{q_F}{V}S_{OF}-\frac{q_F+q_R}{V}S_O+q_R\frac{Y_H-1}{Y_H}\hat{\mu}(\frac{Ss}{Ks+Ss})(\frac{So}{K_{OH}+So})X_H+\\
&a(1-e^{-\frac{q_A}{b}})(\mathrm{S}_{\mathrm{O},sat}-S_O)\\
&\frac{dX_H}{dt}=\frac{q_F}{V}X_{HF}-\frac{q_W}{V}(\frac{q_F+q_R}{q_W+q_R})X_H-\frac{\hat{\mu}_H}{Y_H}(\frac{Ss}{Ks+Ss})(\frac{So}{K_{OH}+So})X_H+\\
&(1-f_p)b_H X_H
\end{aligned} \tag{1}$$

III. FUSION OF BP NETWORKS BASED ON SVM

a. Classifying of input data based on SVM

Suppose sample data $\{x_i, y_i\}(i=1,\ldots,l)$ is present. Among them, $x_i \in R^n$ are n-dimension sample input, $y_i \in R$ are sample output, then the classification is to find a function f through sample training the x except for the training sample could find out corresponding y through f . $\varepsilon-insensitive$ loss function $L^{\varepsilon}(x,y,f)$ is defined as follow:

$$L^{\varepsilon}(x,y,f)=|y-f(x)|_{\varepsilon}=\begin{cases}0 & |y-f(x\le\varepsilon)| \\ |y-f(x)|-\varepsilon & else\end{cases} \tag{2}$$

Where f is a real value function on the field X. The new loss function describes a sort of ε insensitivity model that if the difference between predicted value and actual value is less than ε , and the loss equals to 0.

We can search a sort of estimate regression function in linear function set, it is shown in the formula (4):

$$f(x)=<w\cdot x>+b \qquad w,x\in R^n, b\in R \tag{3}$$

Where $(x_1,y_1),\cdots,(x_l,y_l)$ are independent identically distributed data, b is deflection value. The purpose of regression estimate is to find appropriate w and b to make sure that x except for sample can satisfy $|f(x)-<w\cdot x>-b|\le\varepsilon$. For make sure the optimization problem have solution, slack variable $\xi,\hat{\xi}$ is introduced. Computing the parameter in the formula(3) is equivalent to solve the optimization problem as follow:

$$\min \varphi(x) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \hat{\xi}_i)$$
$$subject \quad to \begin{cases} y_i - (< w \cdot x_i > + b) \le \varepsilon + \xi_i \\ (< w \cdot x_i > + b) - y_i \le \varepsilon + \hat{\xi}_i \\ \xi_i, \hat{\xi}_i \ge 0 \qquad i = 1,\dots,l \end{cases} \tag{4}$$

Where C(C>0) is a constant called penalty factor which be used to express the compromise between the smoothness of function f and the value of that allow error is greater than ε. It mainly react on regulate and control between how to enhance the generalization capacity and decrease the error. ε is a positive number and need enactment in advance, it is mainly used to control the precision of algorithm hoping achieve. The form of $\varepsilon - insensitive$ loss function is shown is formula (7).

We use Lagrange function to translate the original problem to its dual problem:

$$\max Q(\alpha - \hat{\alpha}) = -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \hat{\alpha}_i)(\alpha_j - \hat{\alpha}_j) < x_i \cdot x_j > \\ -\varepsilon\sum_{i=1}^{l}(\alpha_i + \hat{\alpha}_i) + \sum_{i=1}^{l} y_i(\alpha_i - \hat{\alpha}_i) \tag{5}$$

$$\text{Subject to} \begin{cases} \sum_{i=1}^{l}(\alpha_i - \hat{\alpha}_i) = 0 \\ \alpha_i, \hat{\alpha}_i \in [0, C] \end{cases} \tag{6}$$

After solve above problems, we can get w and the estimate function:

$$\begin{cases} w = \sum_{i=1}^{l}(\alpha_i - \hat{\alpha}_i)x_i \\ f(x) = \sum_{i=1}^{l}(\alpha_i - \hat{\alpha}_i) < x_i, x > + b \end{cases} \tag{7}$$

Where x_i which correspond to $(\alpha_i - \hat{\alpha}_i) \ne 0$ is support vector, variable w reflects the complexity of the function. Computation complexity of function estimate by support vectors is irrelevant with dimension of input space and only depends on the amount of support vectors, deflection value b can be calculated through KKT (Karush-Kuhn-Tucker)condition.

We use kernel function $k(x, x^{'})$ to replace dot product, the regression function in the formula (7) changes to:

$$f(x) = \sum_{i=1}^{l}(\alpha_i - \hat{\alpha}_i)k(x_i, x) + b \tag{8}$$

The kernel function $k(x, x^{'})$ is radial basis function.

$$K(x, x_i) = \exp\left\{ -\frac{|x - x_i|^2}{s^2} \right\} \tag{9}$$

Classification of effluent quality data of the sewage treatment plant based on SVM is a black-box, which is based only on input-output measurements of sewage treatment process. In the classification procedure, the relationship between input and output of the sewage treatment plant can be emphasized while the sophisticated inner structure is ignored. Input and output vectors, $\mathbf{x}$ and y act as the learning samples of the prediction model. By learning the samples, the classification model could provide output flag value or new input vector $\mathbf{x}$. The algorithm of classification mainly has two steps.

(1)Set threshold of sewage quality parameters to be predicted, and classify and sign the samples according to the threshold.

(2)Train the SVM, get a data set $\{\mathbf{x}_i, y_i\}, i = 1, 2, .., n$, where $\mathbf{x}$ is input data, n is numbers of samples, and $y \in \{0,1\}$ is flag value of input data.

b. Prediction of sewage quality parameters based on BP network

BP network is a kind of feed forward neural network. It includes input layer, hidden layer, output layer. Assume that the input layer of BP network has M nodes, the output layer of BP network has L nodes, and there is only one hidden layer which has N nodes. Generally, N is larger than M and M is larger than L. Assume $a_i (i = 1,2,\ldots,M)$ is output of the Neurons of input layers, $a_j (j = 1,2,\ldots,N)$ is output of the Neurons of input layers, and $y_k (k = 1,2,\ldots,L)$ is output of the Neurons of input layers, y_m is the output vector of neural network, y_p is the expected output vector, following equations can be acquired.

The ith node of input layer is $net_i = \sum_{i=1}^{M} x_i + \theta_i$,where $x_i (i = 1,2,\ldots,M)$ is the input of neural network, θ_i is the threshold of the ith node.

The jth node of hidden layer is $net_j = \sum_{j=1}^{N} w_{ij} a_i + \theta_j$,where $w_{i,j}$ is the weight of hidden layers, θ_j is the threshold of the jth node.

The kth node of output layer is $net_k = \sum_{k=1}^{L} w_{jk} a_j + \theta_k$.

The BP network for predicting sewage quality parameters is shown in figure2.The learning algorithm is shown as followed.

(1) Initialization: All weighted coefficients are set as the smallest random numbers.

(2) Provide training set.

(3) The output of each neuron in the hidden layer and the output layer is calculated.

(4) Calculate the error between the expected value and the output value.

(5) Adjust the weighting factor of the output layer.

(6) Adjust the weighting factor of the hidden layer.

(7) Return (3) until the error meets the requirements.

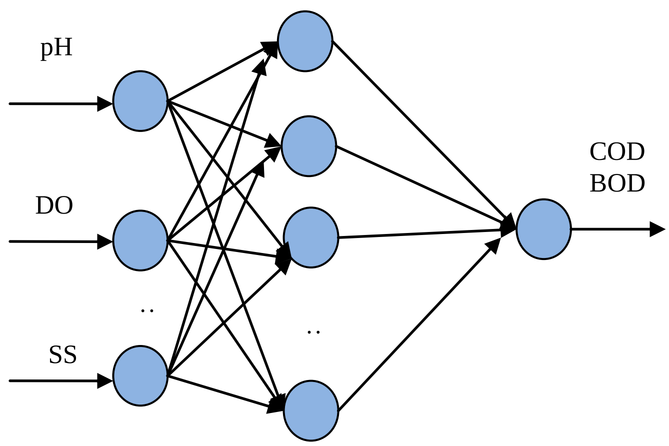

Figure 2. BP network for predicting sewage quality parameters

c. Fusion of BP networks based on SVM

It is possible to fall into local extremum when BP network is trained. The approximation capability and generalization of BP network have a close relation with typicality of training samples. The SVM are sensitive to missing samples and it cannot present a general solution for nonlinear problem.

During sewage treatment process, there is a serious coupling relation among each parameters. Except this, because the biological and chemical reaction are involved in the sewage treatment process, the prediction parameter COD and BOD do not have a one-to-one correspondence relation with the parameters of the sewage quality parameter. The training of BP network will be failed when input data are same or similar while there is a great difference between output data. We present an fusion algorithm based on SVM and BP network. The input data is classified by the SVM, which makes different kind of data enter different BP network. The BP networks are

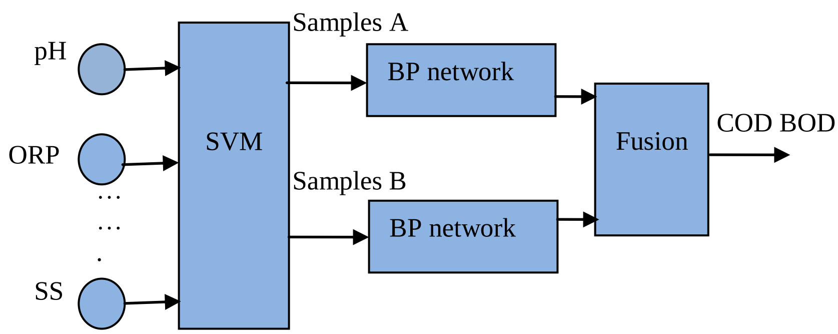

Figure 3. Fusion of BP networks

trained respectively by different samples. The output prediction values of two BP networks are fused by following equation.

$$COD = \sum_{i=1}^{2} w_i COD^{BP_i} \tag{10}$$

$$BOD = \sum_{i=1}^{2} w_i BOD^{BP_i} \tag{11}$$

IV. EXPERIMENT RESULTS AND ANALYSIS

According to above mentioned algorithm, we use fusion of two BP networks to predict sewage quality parameters. The test results is presented and discussed. Before classifying and training and learning of the input data, there are data preprocessing in our work, i.e. the eliminating of outliers and PCA analysis of input data.

a. Eliminate of outliers

To eliminate outliers of the data, a novel clustering algorithm[8] is adopted in this paper. In this method each object is assigned to the cluster of its nearest neighbor within a certain distance. The distance is called mmd(minimum mean distance).

Given a set of n objects y1, y2, …, yn, in a d dimensional space which refers to the number of measurement variables, the mean minimum distance (MMD) is defined as formula 1.

$$\mathrm{MMD}=\frac{1}{n}\sum_{i=1}^{n}\min_{j\neq i}\left[\left(\sum_{k=1}^{d}(y_{ik}-y_{jk})^2\right)^{1/2}\right] \tag{12}$$

If the distance between an object and its' nearest point is larger than 2*MMD, then the object is defined as an outlier. The algorithm successfully distinguished outliers from normal data as shown in figure4,5.

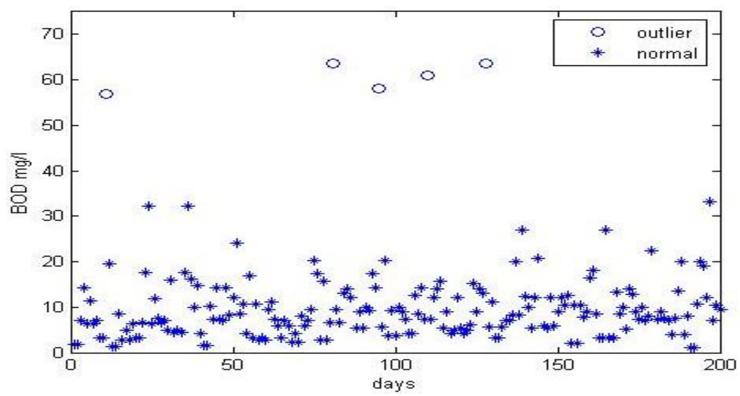

Figure 4. Part of Influent BOD

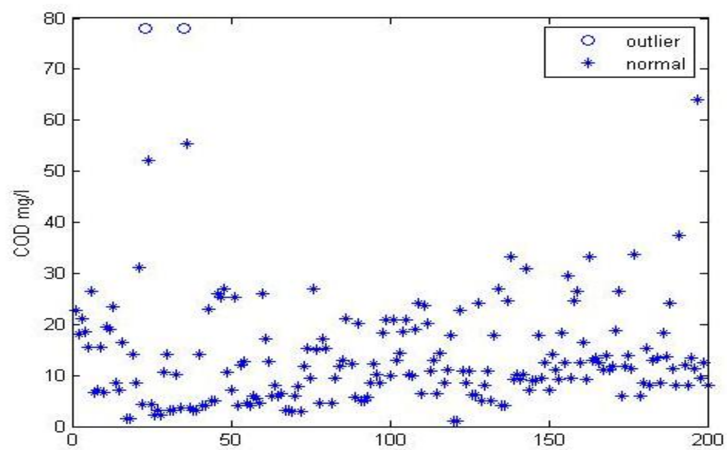

Figure 5. Part of Influent COD

b. PCA(Principal Component Analysis) of sewage data

In practice, COD (chemical oxygen demand) and BOD (SS) are important indices of water quality. And they are difficult to measure on-line. So we selected COD and BOD as sewage quality parameters to be predicted.

During the process of sewage treatment, the DO (dissolved oxygen) and ORP (oxidation-reduction potential) are used to optimize adjust the aeration quality and the PH value is used to judge whether the systematic alkalinity be suit and be good for microbe’s growth at the aerobic stage. At the anaerobic stage, the PH value and ORP not only provide the control information of the de-nitrification process, but also can act as the means of input amount. The interrelated experiment results indicated that the ORP, DO and PH value correlate with COD concentration in CASS reaction stage, especially in the situation that the air quantity is invariable and COD is hard to be degraded anymore, the ORP and DO value rise rapidly and then they will turn to be stationary and level off in a certain high-value range. The PH value rises continuously till the COD stop degraded. Except this, temperature and MLSS (mixed liquid suspend solids) also has co-relation with COD and SS. So we select the ORP, DO, PH, MLSS, temperature and COD, BOD, SS of influent as elements of variable x, input of prediction model based on SVM, as shown in Figure 2.

According to the corresponding responses between the sewage quality parameters to be predicted and different influent sewage parameters, PCA is utilized to select the characteristic parameter that have a close relation with the sewage quality to be predicted. The step is shown as followed.

(1) The standardization of the input data $X_{n\times m}$. $X_i^* = (X_i - E(X_i)) / (\mathrm{var}(X_i))^{1/2}$

(2) Calculate the principle component value by singular value decomposition. If $X_{n\times m}^*$ is the standardized input data, then $X^* = U\sum V^T$,where $U_{n\times n}$ and $V_{m\times m}$ are orthogonal matrixes consists of singular vectors, Σ is Diagonal matrix consists of singular values, i.e. Σ =diag(δ 1, δ 2,⋯,δ n).

Compute variance of each principle component：λ i=δ i/(n-1).

Compute Percentage of cumulative variance :

$$CPV(k) = \frac{\sum_{i=1}^{k} \delta_i^2 / (n-1)}{\sum_{i=1}^{n} \delta_i^2 / (n-1)} \tag{13}$$

(3) Find the all of the percentage of cumulative variance that is larger than a given value, determine the principal component and reduce the dimension of input data.

The analysis results of PCA of sewage data is shown in table 1. From table 1, it can be seen that 84.968 percentage information of influent quantity, PH, SS, DO, ORP can be represent by three principle components. According to table2, DO, ORP, and PH that respectively has strong relations with principle component1, 2, 3 have been selected as input as BP network.

Table 1: Results of PCA

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	2.054	41.072	41.072
2	1.342	26.830	67.902
3	.811	16.228	84.131
4	.603	12.064	96.195
5	.190	3.805	100.000

Table 2: Correlation between each variables and principal component

	Component		
	1	2	3
V1	-.149	.817	.238
V2	.276	-.655	.647
V3	.538	.490	.488
V4	.914	-.027	-.221
V5	.912	.070	-.224

c. Prediction by BP networks

Biology-chemical energy consumption process including biological and chemical reaction is a severe nonlinear process. As a kind of artificial neural network, back propagation network has good fitness for nonlinear function. Here, we used BP network to set the model. As shown in figure 2, the model has one hide layers. The hidden layer has 15 cells. We trained the model with 70 samples, test the model with other sets of datum.

Table3: Training results of Bp network

COD		MSE		c	σ^2
training samples	test samples	training samples	Test samples		
32	30	0.9982	1.02640	32	0.0625
80	80	0.9082	0.90264	40	0.125
BOD		MSE		c	σ^2
training samples	test sample	training samples	test sample		
32	30	0.22	0.2774	32	0.0625
80	80	0.212	0.324	40	0.125

From Table3, we can see the mean squared errors of test samples of the prediction model are small. It shows that the prediction model based on BP networks make good performance in effluent quality prediction for sewage treatment plant of CASS process. When the numbers of training samples is changing, the varied range of mean squared errors is small. It shows that the degree of depending on the sample of the prediction model is small, i.e., the prediction model based on SVM has good generalization performance and small samples learning ability.

It is also concluded that energy costing of a sewage treatment plant with CASS process mainly is dependent on influent in aeration tank. COD and BOD of the sewage treatment plant could be predicted acutely by influent PH, ORP and DO in aeration through a BP network model.

d. Fusion of BP networks based on SVM

In this part, we predicted COD and BOD during certain period respectively with fusion model of BP networks and single BP networks. The prediction results of COD by fusion BP networks are shown in figure 7. The prediction results of COD by single BP networks are shown in figure 8. The prediction results of BOD by fusion BP networks are shown in figure 10. The prediction results of BOD by single BP networks are shown in figure 11. Figure 6 shows the measured value of COD. Figure 9 shows the measured value of BOD. From the results, it can be seen that BP networks have a good capability in prediction of the sewage quality parameters. It also can be concluded that during prediction of sewage quality parameters, fusion of BP networks improve the stability and learning precision of the BP networks.

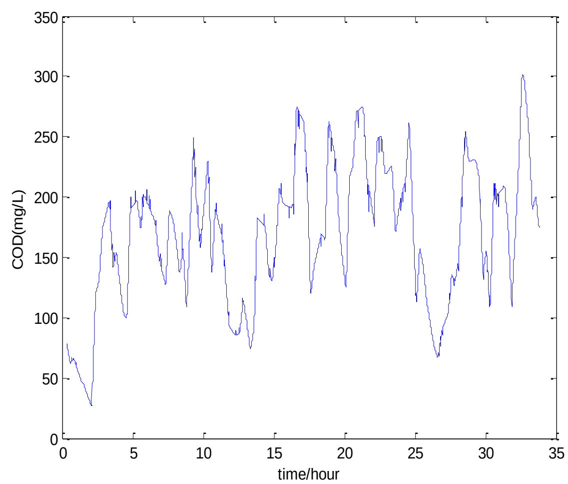

Figure 6. Measured value of COD

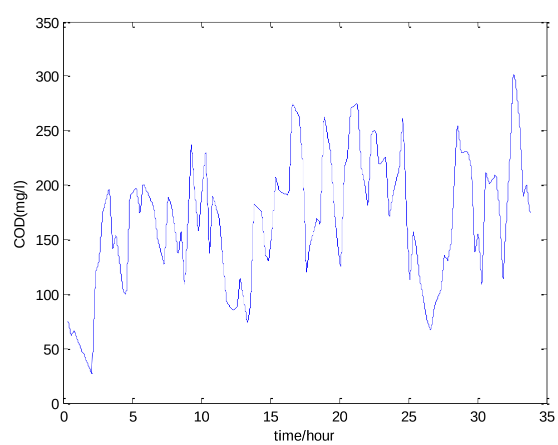

Figure 7. Prediction of COD by fusion of BP networks

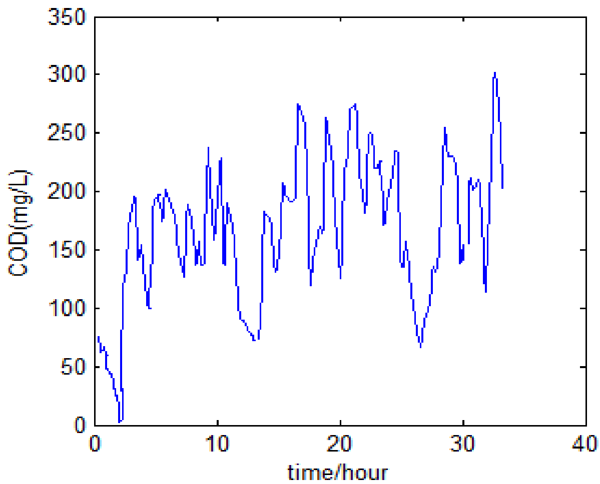

Figure 8. Prediction of COD by single BP network

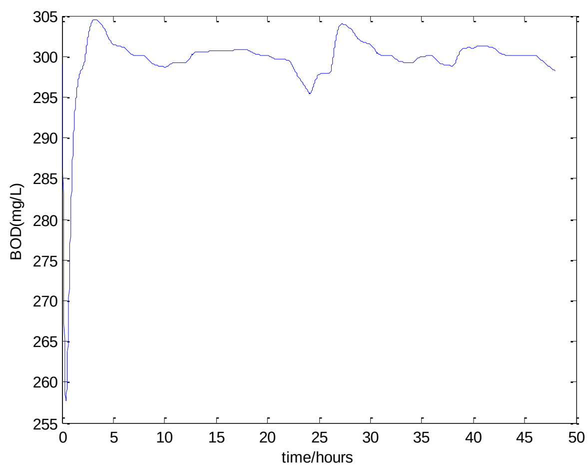

Figure 9. Measured value of BOD

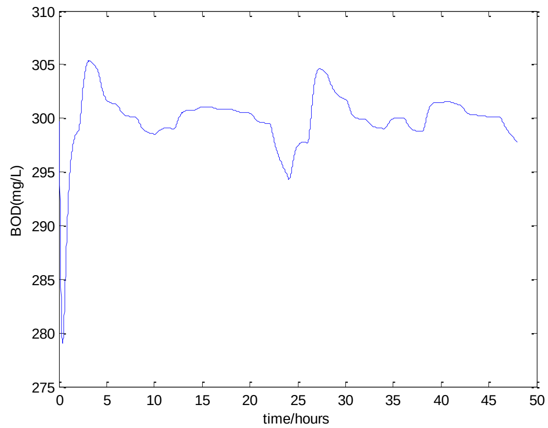

Figure 10. Prediction of BOD by fusion of BP networks

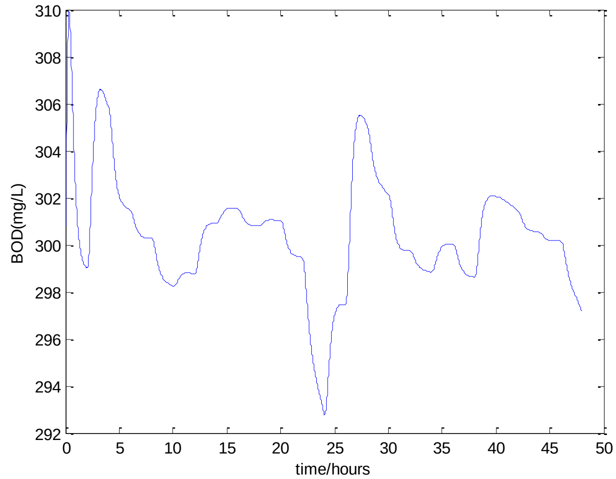

Figure 11. Prediction of BOD by BP network

V. CONCLUSIONS

In this paper, a prediction method of sewage quality parameter COD and BOD based on BP network fusion is presented. The BP network fusion is based on SVM. The BP network fusion improves the stability and precision of the training, and overcome the disadvantages of single BP network. During the prediction process, the input data firstly are classified into two kinds by SVM according to their characteristics. Before classifying, the outliers of the input data has been deleted by a clustering method; and the correlation among parameters are analyzed which is used to reduce the dimension of the input data, acquiring the parameter that have a close relation with the parameter to be predicted. After classifying, the input data are classified into two kinds, and the BP network are trained by the corresponding data. The prediction value of the parameter COD and BOD are predicted with the fusion value of two BP networks. The test results shows that the prediction error of fusion method is less than prediction error of common BP network. Except this, the training stability of BP network are also improved.

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